Spatial interpolation of daily meteorological data

A knowledge-based procedure for the region of the European Communities

P. van der Voet
C.A. van Diepen
J. Oude Voshaar

Report 53.3

DLO Winand Staring Centre, Wageningen (The Netherlands), 1994

ABSTRACT

P. van der Voet, C.A. van Diepen en J. Oude Voshaar, 1994. *Spatial interpolation of daily meteorological data. A knowledge-based procedure for the region of the European Communities.* Wageningen (The Netherlands), DLO Winand Staring Centre. Report 53.3; 118 pp.; 5 Figs; 9 Tables; 9 Annexes.

A calculation procedure is described for interpolating daily weather data within the European network of meteorological stations. Historical daily meteorological data over a period of five years for 275 stations were used. The procedure consists in selecting the optimum set of at most four stations, followed by interpolation through averaging the daily values at the selected stations. The selection of the optimum set of stations for a point involves proximity, similarity in terms of altitude and distance to the coast, the position in relation to climatic harriers, the degree to which the stations surround that point, and the number of stations of a set.

Keywords: calculation procedure, linear interpolation, meteorological station, weather data

ISSN 0927-4537

The DLO Winand Staring Centre is continuing the research of: Institute for Land and Water Management Research (ICW), Institute for Pesticide Research, Environment Division (IOB), Dorschkamp Research Institute for Forestry and Landscape Planning, Division of Landscape Planning (LB), and Soil Survey Institute (STIBOKA).

Project 7220 [Rep53-3.HM + .AX3/02.1995]

Contents

Tables

Figures

Preface

This report, prepared by the DLO-Winand Staring Centre in Wageningen, the Netherlands, describes the procedure for interpolating daily weather data within the European network of meteorological stations and the validation of this procedure. It is the third in a series on spatial interpolation of daily meteorological data. The first two reports by Eric Beek dealt with the theoretical evaluation of available techniques for the spatial interpolation of meteorological parameters, and the application of kriging to predict rainfall in a few test cases. The development and validation study in this report was carried out in 1992, and a draft report was available in January 1993. The completion of the report was then delayed because the first author took up another assignment. A final draft was ready by November 1994. Whereever feasible, references has been updated, but the general context described in this report is the one in 1992. The study made use of historic daily meteorological data over a period of five years for 275 stations in the 12 EC countries and some adjacent countries. The procedure has been designed for the specific purpose of estimating weather data on a 50 x 50 km grid over the E.C. for use as input data for a crop growth simulation model, but the procedure has universal validity for spatial weather interpolation, as demonstrated by the validation study.

The study was carried out in 1992 as part of a contract study to develop a Crop Growth Monitoring System for the Joint Research Centre (JRC-Ispra Site) of the Commission of the European Communities. The methodology makes use of agrometeorological models, e.g. crop growth simulation models, for yield forecasting purposes. This is done in the framework of the JRC pilot project for the Application of Remote Sensing to Agricultural Statistics, also called Agriculture Project, or MARS Project (Monitoring Agriculture by Remote Sensing). This project is carried out by the Agricultural Information Systems Unit of the Institute for Remote Sensing Applications of JRC, in support to the Statistical Office of the EC (EUROSTAT) and to the Directorate General for Agriculture of the EC (DGVI). Within the Agriculture Project the crop modelling is organized under Action 3 Yield Forecasting Models.

The authors are indebted to Ben van der Pouw for his sustained encouragement and critically reviewing earlier drafts of this report. The study has benefitted from the continuous professional and constructive support of Arnold Bregt. We acknowledge the contribution of Gert Jan Reinds on data handling, Jandirk Bulens on map compilation, IJke van Randen on optimizing calculation procedures, and Bert Sterling for designing specific FORTRAN tools.
Many thanks are also due to Paul Vossen (JRC) for his kind support and counsel.

Paul van der Voet
Kees van Diepen
Jan Oude Voshaar

Summary

In the framework of Action 3 of the 'Agriculture Project' of the Joint Research Centre (JRC) the Winand Staring Centre is developing a system for regional crop growth monitoring (CGMS) over the whole of the European Communities (EC).

It is assumed that meteorological factors explain year to year variation in production. Therefore the system makes use of weather data as determining factors for crop growth and crop production. This concerns daily weather data on radiation, temperature, rainfall, windspeed and humidity. Such weather data can be fed into the crop growth model WOFOST to calculate per simulation run the growth of a given field crop on a given location in a given year. Daily weather data were available in a historic data base called DBMETEO on about 360 stations. The areal unit for zones wherein the weather is considered as homogeneous is a square grid cell of 50 km x 50 km. The land area of the EC is covered by 1389 of these grid cells.

The purpose of this study is to develop and validate an algorithm to estimate the daily weather in each of the grid cells from the weather data of the stations. This weather on grid cells should be sufficiently accurate to serve as input to the crop growth model. Furthermore JRC stipulated that the weather on gridcells should be realistic itself. The algorithm has been implemented in the Crop Growth Monitoring System.

In a preparatory study it was concluded that the prospects of applying simple linear interpolation techniques would yield satisfactory results for all variables but rainfall (Beek, 1991). The simple techniques include application of Thiessen polygons to assign values of the nearest weather station to a location, application of the technique of moving averages or of weighted moving averages such as the 'inverse distance' method, using the values of several neighbouring observation stations.

Rainfall is known to show more spatial and temporal variation than the other weather variables. It was concluded on theoretical grounds that kriging could be promising for rainfall, but it was expected that a method based on kriging for the whole of the EC would also meet a considerable amount of (computer) technical problems. Therefore the practical application of kriging was not implemented within the framework of the current project on agrometeorological yield models. It was decided to concentrate on the simpler linear interpolation techniques for rainfall as well.

In another preparatory study (Van den Brink et al., 1991) it was pointed out that important weather characteristics related to crop growth modelling are the number of rainy days and total rainfall per time period. These characteristics appeared to be best estimated with the rainfall data of only one station as interpolation with more stations leads to a considerable averaging effect, resulting in an overestimate of the number of rainy days.

In the present study a knowledge-based procedure is proposed to predict daily meteo data. The procedure consists of the selection of the optimum set of at most four

stations to be used in the interpolation, followed by the interpolation through averaging of the observed daily values at the selected stations without weighting for distance.

The selection of the optimum set of stations involves several criteria: proximity, similarity in terms of altitude and distance to the coast, the position in relation to climatic barriers, the degree to which the selected stations are surrounding the location, and the number of stations of a set.

The criteria are combined and quantified by calculating difference-scores for pairs of observed and estimated values for a point. In the case of several observations, the criteria are quantified by a score for a group of point observations and point estimations.

While developing the selection procedure different alternatives had to be compared. For the evaluation of these alternatives all suitable stations in or close to the EC were used (except for the stations in Italy). For all these stations the observed data were compared with the predictions using the other stations (the leave-one-out method).

As criterion for evaluating the accuracy of the estimated result the root mean squared error (RMSE) between observed and predicted values has been used. For each individual station the RMSE was determined for all alternative station selections.

In addition, for every station separately it has been computed (per variable) which set of at most four stations gives the best estimate, i.e. has the lowest RMSE value. Division of the RMSE by the RMSE of this best set, gives the relative RMSE of all alternative selection procedures. After averaging over the four most important variables (radiation, sunshine duration, minimum temperature and maximum temperature) and over all stations in a region, a country or the EC, the alternative selection procedures can be compared on the basis of the regional mean of the average relative RMSE over the four variables. The procedure with the lowest average RMSE has been identified.

The performance of the station selection algorithm was evaluated by comparing the results obtained with six alternative selection rules, followed by either averaging without weighting for distance or by inverse distance interpolation methods with several weighting powers.

It was found that if a fixed number of stations was used in the interpolation, the use of two stations lead to a large improvement in interpolation results as compared to the use of only one station. Increase from two to three stations gives a small additional improvement, and from three to four stations there is hardly any improvement. Some further improvement is obtained by taking into account the similarity of the stations in terms of altitude and distance to the coast. If more expert knowledge is built into the station selection procedure by stipulating that the stations in the set should be located around the reference station in a regular pattern, and by assigning penalties to stations for differences in altitude, for differences in distance from the coast, and for position on the other side of climatic barriers, the interpolation result improves again. The number of stations in the optimum set may be variable between one and four.

Applying weighting rules for distance does not improve the results any further. The interpolation results varied somewhat between variables. The best results were found for radiation and sunshine data (correlated), followed by temperature and humidity. The results for windspeed were clearly worse than for the other variables.

Finally some country effect was found. For the countries situated in the temperate zone better results were found than for the countries in the mediterranean zone. The larger countries gave better results than the smaller countries. Within the temperate zone the best results with the interpolation procedure were obtained for the United Kingdom, the poorest results for the Netherlands.

In order to validate these results, the computations have been repeated for an independent set of stations, i.e. the stations in Italy. They were not yet available while developing the algorithm.

1 Introduction

1.1 Background and aim

In the framework of Action 3 of the 'Agriculture Project' of the Joint Research Centre (JRC) the Winand Staring Centre is developing a system for regional crop state monitoring over the whole of the European Communities (EC).

It is assumed that meteorological factors explain year to year variation in production. Therefore the system makes use of weather data as determining factors for the crop growth and crop production.

Weather data ared used in two ways:
- indicative, which means that weather data themselves serve as indicators;
- integrated, all weather data are evaluated for their combined influence on crop growth by feeding them as daily input parameters to a dynamic crop growth model.

The system makes use of the crop growth model WOFOST (Van Diepen et al., 1989, Hijmans et al., 1994, Supit et al., 1994). This model calculates the growth and production of an annual crop, growing under given weather conditions. For a defined crop, the model calculations are carried out per year and per location. The WOFOST model is used to derive crop state variables serving as indicators for the evolution of the current agricultural season. The results of simulation of crop growth for historic years serve as reference values.

The dynamic simulation model needs daily weather data on radiation, temperature, rainfall, windspeed and humidity. The areal unit for zones wherein the weather is considered as homogeneous is a square grid cell of 50 km x 50 km. The land area of the EC was covered by 1389 of these grid cells (Fig. 1).

At the time of the study the EC was joined by 12 countries, not including East Germany.

Daily weather data are collected in a historic data base called DBMETEO (Reinds, 1991) on about 360 stations with generally 15 to 30 years of data (van der Drift and van Diepen, 1992), and in a current year data base on about 650 stations.

The purpose of this study is to develop an algorithm to estimate the daily weather in each of the grid cells from the weather data of the stations. First of all this weather on grid cells should be sufficiently accurate to serve as input to the crop growth model. As a more objective requirement the JRC stipulated that the weather on gridcells should be realistic itself, i.e. showing a representative day-to-day variation.

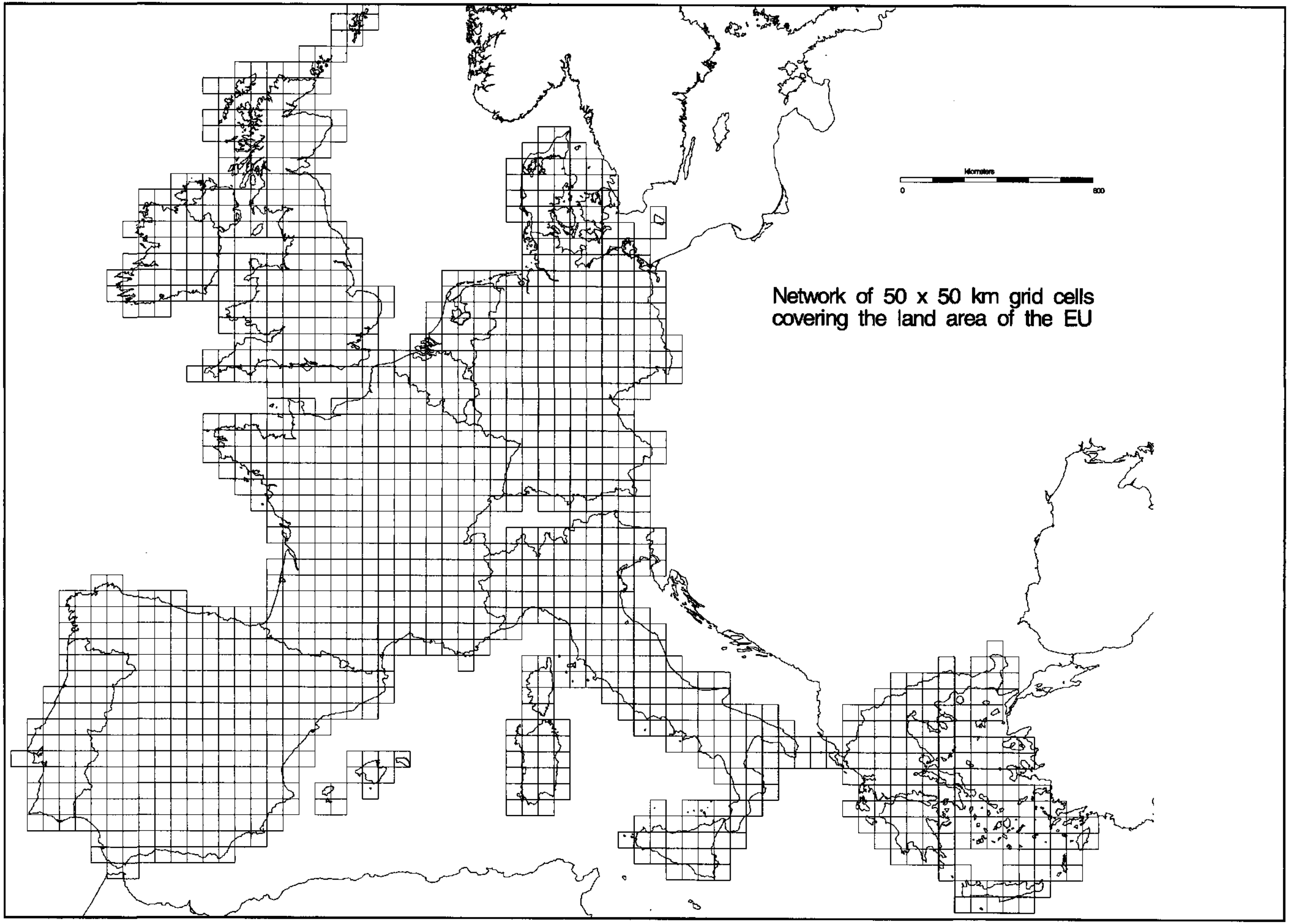


Fig. 1 Network of 50 km x 50 km grid cells covering the land area of the EC

1.2 Overview and results from preparatory studies

Some preparatory studies have been carried out to identify appropriate techniques for the spatial interpolation of these daily meteorological station data.

In (Beek, 1991-1) an overview is given of the main spatial interpolation techniques. They can be divided into global and local techniques.

Global techniques such as Trend Surface Analysis and Fourier series interpolate values with the use of all available data.

Local techniques such as Thiessen polygons, (weighted) Moving Averages, Splines, and Kriging estimate values from neighbouring points only.

Common meteorological practise is to use *Thiessen polygons* that assign the values of the nearest weather station to a location.

An other interpolation method which is often applied makes use of *moving averages.* The method uses a window to achieve an interpolation of values within an area. The size of the window either emphasizes or rules out short range variations.

The technique of weighted moving averages allows to assign some values more influence on the interpolated value than other values: the most common 'inverse distance' method diminishes the influence of values with increasing distance.

Splines are piecewise (polynomial) functions that are exactly fitted to a small number of data points while at the same time ensuring that the joins between one part of the curve and another are continuous. It is useful to obtain a quick and aesthetic visualization of a variable, but its calculated values are not very accurate.

Kriging is based on the assumption that spatial variation of a regionalized variable is too irregular to be modelled by a mathematical function, but can be described more appropriately by a stochastic distribution. The interpolation procedure proceeds exploring and then modelling stochastic aspects of the regionalized variable. The resulting information is then used to estimate weights for interpolation.

Some of these local techniques can be extended in order to use information of extra variables like distance from the coast and altitude. For instance cokriging uses the information of such 'covariables'.

Considering the spatial and temporal scale of the meteorological processes Beek (1991-1) expects simple linear interpolation techniques to yield satisfactory results for the variables sunshine duration, radiation, temperature, windspeed and relative humidity.

Rainfall is known to show more spatial and temporal variation. Therefore a special study was carried out to investigate the spatial variability of daily precipitation amount in relation to meteorological conditions (Beek, 1991-2; Beek et al., 1992).

Four different weather conditions at four selected days in 1984 in North-western Europe were investigated. Rainfall data were interpolated using kriging. The interpretation of the involved parameters increased the understanding of the spatial behaviour of daily rainfall. Large differences in the spatial structure of daily rainfall were observed as a result of different meteorological conditions. Stratification of the study area into a coast, a mountain and an interior stratum reduced the Mean Squared Error of Prediction considerably.

Within the limited range of this study it appeared to be possible to interpolate rainfall using kriging. Semi-variograms were computed for every location for every day.

A further development towards an operational interpolation system for daily weather based on kriging for the whole of the EC is expected to meet a considerable amount of (computer) technical problems. It would involve the daily computation of regional semi-variograms for every variable. For the time being the practical application of kriging was not implemented within the framework of the current project on agrometeorological yield models. It was decided to concentrate on the simpler linear interpolation techniques for rainfall as well.

A preliminary study (Van den Brink et al., 1991) compared the performance of the interpolation using several (weighted) moving average techniques, including the Thiessen approach. The study involved regions in Northern Germany, Central Germany, and Southern/Central Spain.

From the results in the three test regions the following conclusions were drawn:
- With regard to the number of stations, it appeared that interpolation using two or more stations gave better estimation results as compared to substitution using one station.
- The best results were obtained when the number of stations was 3, 4, or 5. On the other hand, to minimize the effect of smoothing, it was recommended to use as few stations as possible.
- Little differences in interpolation results were observed from varying the value of the exponent in the distance weighting functions. As no preference for one of these weightings can be formulated on a physical basis, a zero value for the exponent was recommended, implying no weighting for distance.
- It appeared that no significant differences exist between seasonal and yearly based evaluations of the interpolation methods.
- Important weather characteristics related to crop growth modelling are the number of rainy days and total rainfall per time period. These characteristics appeared to be best estimated with the meteo data of only one station.
- Furthermore it was suggested that the interpolation can be improved by selecting stations that are similar with respect to altitude and distance to the coast.

The conclusions of the preliminary study are indicative, because they are based on a relatively limited number of test cases. In particular it was not made clear how a set of 3, 4 or 5 stations could be selected from all theoretically possible sets, or how geographic similarity with respect to altitude and distance to the coast could be quantified.

1.3 Specific aim of the present study

The present study aims at developing and validating an operational interpolation procedure based on the findings of the preliminary study.

This involves:
- quantifying criteria for the selection of a set of stations to be used for the interpolation of daily meteo data from stations to a grid cell.
- translating the criteria into an algorithm suited for automated implementation, with modest computing time requirements.
- developing the station selection procedure by comparing its interpolation results with the results of all other possible alternative station selections.
- comparing the interpolation results of several alternative interpolation methods when applied to large regions such as countries or the whole EC-area.

Therefore, a knowledge-based interpolation method has been developed using the idea of selecting geographically similar stations. This method could be regarded as a counterpart of cokriging. Cokriging cannot be implemented for such large data sets, but the proposed method uses the same extra geographic information.

1.4 Outline of this report

The procedure was developed in an iterative way, but Chapter 2 starts with a description of the final version, consisting of the selection of the optimum set of stations to be used in the interpolation, followed by the interpolation through averaging of the observed daily values at the selected stations without weighting for distance.

The selection of the set of stations involves several criteria: proximity, similarity in terms of altitude and distance to the coast, the position in relation to climatic barriers, the degree to which the selected stations are surrounding the location, and the number of stations of a set.

Several alternative methods of selecting stations are compared with the final version. In some alternatives altitude, distance to the coast or climatic barriers are omitted during the selection stage. Also simpler procedures selecting a fixed number of (1 to 4) stations are considered. Furthermore alternatives are used with inverse distance weighing.

In order to compare alternative procedures the prediction error is used.

Since no observations are available for the grid cells of 50 km x 50 km, applying the interpolation procedure on these grid cells does not enable a comparison of predicted and observed data. Therefore the leave-one-out method is used by applying an interpolation procedure to a reference station. The reference station is excluded from the collection of stations, and its daily weather values are predicted by means of interpolation using the data of other stations.

The comparison of alternative station selection procedures was first applied to single reference stations. Later, the comparisons were extended to a number of reference stations within specified regions.

The comparison of the alternative methods was carried out for 233 stations in all of the EC except Italy and Greece and for 18 stations in some bordering areas in Switzerland, Austria and Slovenia. Alternative variants of the procedure were tested as well on subregions.

In order to validate these comparisons and the final choice of the selection method, the computations were repeated on an independent set of 24 stations in Italy.

In Chapter 3 the results are presented and discussed. Chapter 4 contains the conclusions and evaluation, justifying the choice of the algorithm.

2 Methodology

An interpolation procedure for estimating daily weather data on a regular grid has been developed and validated. Section 2.1 describes the meteorological data and the grid that have been used, Section 2.2 the interpolation procedure and Section 2.3 the statistical validation method. In Section 2.2.1 the interpolation method is given. Rainfall is estimated by using the data of the station that is most similar to the centre of a grid cell. In Section 2.2.2 the criteria for selecting such a single, most similar station are quantified. The other variables are estimated by selecting a set of stations. In Section 2.2.3 criteria are quantified to select such a set of stations. During the process of identifying the best selection algorithm various alternatives were compared. Section 2.2.4 describes some alternative procedures. Section 2.3 describes the method applied for the statistical validation of the interpolation results. In Section 2.3.1 the method to compare alternative interpolation procedures for a reference point is presented. Section 2.3.2 presents the method to compare interpolation procedures over regions.

2.1 Description of data

The dynamic simulation model needs daily weather data on radiation, temperature, rainfall, windspeed and humidity. The areal unit for zones wherein the weather is considered as homogeneous is a square grid cell of 50 km x 50 km. The land area of the EC was covered by 1389 of these grid cells (Fig. 1).

At the time of the study the EC was joined by 12 countries, not including East Germany.

Daily weather data are collected in a historic data base called DBMETEO (Reinds, 1991) on about 360 stations with generally 15 to 30 years of data (Van der Drift and Van Diepen, 1992), and in a current year data base on about 650 stations.

Due to a considerable amount of missing data in the period 1975-1979 (mainly sunshine duration) some (mostly Spanish) stations are excluded from the comparison. The Greek stations are excluded because of the monthly character of the data. The Italian data were not available at that time.

A total number of 233 meteo stations of the United Kingdom, Ireland, Denmark, The Netherlands, Belgium, France, Spain, Portugal, and Germany and 18 meteo stations in some bordering areas in Switzerland, Austria and Slovenia were used as reference stations. The comparisons were then made for all 233 stations together, and countrywise.

Afterwards 24 Italian stations were used as an independent data set to validate the developed procedure. Figure 2 shows the location of all of these 275 stations.

Fig. 2 Location of all meteo stations within DBMETEO suitable for the development and validation

Although the worst stations were already excluded, omissions of up to 60% of the period were found in the interpolation results for some of the remaining reference stations in Spain and Italy, caused by missing values.

The whole EC, except Italy and Greece, including bordering regions in Switzerland, Austria and Slovenia was used to compare alternatives and develop the proposed algorithm. In order to validate the comparisons and the final choice of the selection method the computations were repeated on an independent set of stations, i.e. the stations in Italy. For practical reasons the results of the stations used for the development of the algorithm, and the results of the (Italian) stations that were used for the validation of the algorithm are presented in the same Tables and Figures.

2.2 Interpolation procedure for daily weather data

2.2.1 Outline of the procedure

A procedure has been designed to provide an estimate of daily weather data *on a regular grid* on the basis of station data. The estimation differs for the various variables. The stations to be used for the estimation of weather on a location are selected from the list of European weather stations, available within DBMETEO (Reinds, 1991).

Rainfall is estimated by using the data of a single station that is most similar to *the centre of the grid cell.* The following criteria are used to select the most similar single station as compared to the location:
o proximity;
o similarity in terms of:
altitude;
distance to the coast;
the position relative to climatic barriers.

The use of more than one station to estimate rainfall by interpolation may improve the mean prediction error of the estimate of the amount of rainfall. However, the averaging effect will overestimate the number of wet days considerably. The temporal distribution of rainfall has a strong influence on the availability of soil water for a crop through its effect on evaporation and percolation. Therefor it was decided to use the rainfall data of only one weather station, in order to achieve a realistic representation of the number of rainy days for the grid cell.

The other variables (on radiation, temperature, windspeed and humidity) are estimated by means of averaging the data of the optimum set of stations, surrounding the centre of the grid cell. The averaging is carried out without weighting for distance. For the interpolation of other weather variables one or more similar stations can be selected. The selection criteria for this set of stations are an extension of the criteria to identify the most similar single station. Besides the already mentioned criteria the following criteria are used:

- o the degree to which the selected stations are surrounding the location;
- o the use of at most four stations;
- o the number of stations in a set.

For the meteo variables minimum temperature, maximum temperature and humidity, the values of the stations to be used for interpolation are corrected for differences in altitude between these stations and the average altitude of the grid cell. Before interpolation all values are adjusted to the average altitude of the grid cell. For every 100 m of increase in altitude a decrease in temperature of 0.6 °C and a decrease in vapour pressure of 2.5% are assumed.

The estimation procedure is universally valid and is applicable to any arbitrary location situated in the area covered by a network of meteo stations. The centre of a grid cell is such an arbitrary location. But also a weather station can be chosen as a location. In the following 'location' is used to indicate the points for which daily weather must be estimated.

2.2.2 Quantification of criteria for selecting one station

The estimation of rainfall involves the selection of a single station on the basis of similarity criteria.

For locations where rainfall has to be estimated the selection of the most similar station is determined by calculation of a 'difference-score'. This difference-score is conceived as a measure of difference between locations, expressed in terms of distance in kilometers. All geographic differences are evaluated empirically in terms of kilometer equivalents and added to the score. The higher the difference-score, the less similarity between a station and the location. If the station is located at the same place as the location, its value becomes 0. For any of the stations S_1, S_2, ..., S_n in DBMETEO and location L this score is defined as follows:

$$DSCORE_i = DIST_i + WALT*DALT_i + DIFCST_i + CLBINC_i \qquad (1)$$

with:

DSCORE$_i$: the difference-score of the station S_i in relation to location L (km);
DIST$_i$: the distance between S_i and L (km);
DALT$_i$: the (absolute) difference in altitude between S_i and L (m);
WALT : the weighting factor for DALT (km/m); the value of the weighting factor WALT determines the relative importance of altitude in comparison with the other criteria like distance. Meaningful values for the weighting factor WALT appear to be around 0.5 (Van den Brink et al, 1991);
DIFCST$_i$: the (absolute) difference in (corrected) distance to the coast between S_i and L (km). This difference is expected to be most important close to the coast and to be of no importance in zones too far from the coast to be climatically influenced by it. Therefore the distance to the coast

of both S_i and L are corrected according to their climatic importance. Figure 3 shows the assumed relation between real distance and climatologically corrected distance to the coast. From Figure 3 can be derived that differences in distance to the coast are considered to be most important within 50 km of the coast and of no influence anymore further than 200 km from the coast. The distance to the coast is calculated by a geographic information system using a generalized coastline, disregarding estuaria and bays;

$CLBINC_i$: an increment of the difference-score in the case that a station S_i is separated by a climatic barrier from location L (km). In practice the increase of the difference-score with a value of 1000 proved to be sufficient to disqualify this kind of stations.

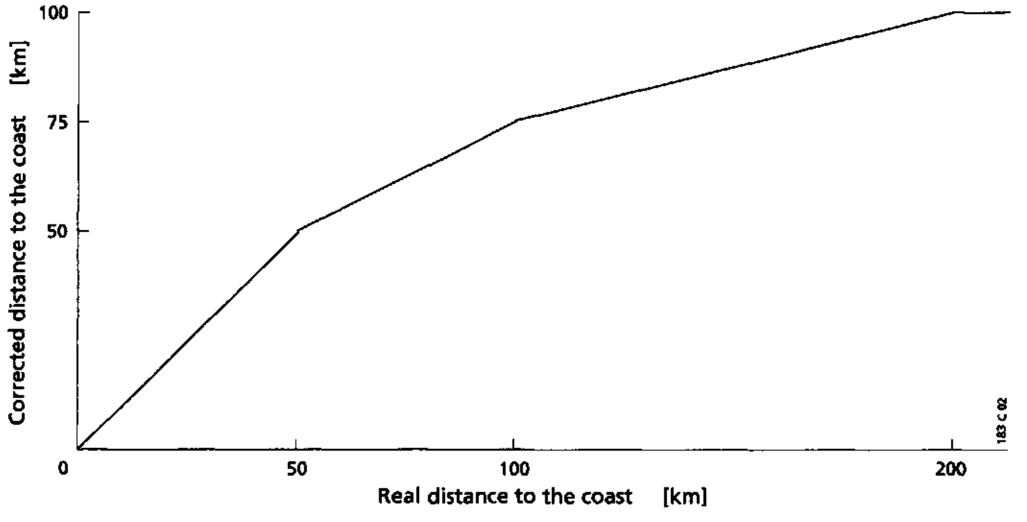


Fig. 3 Assumed relation between real and climatologically corrected distance to the coast

The station with the lowest difference-score is considered the most similar station and the optimum one to be used for the estimation of rainfall at location L.

The effect of the different components of the formula is explained in Annex 1. It contains some figures with examples of two stations and a location L. In Annex 1.1 station S_1 is most similar because it is located nearer to location L. In Annexes 1.2 and 1.3, station S_2 becomes most similar because of respectively less difference in altitude, and less difference in distance to the coast.

If in (1) the terms of altitude, distance to the coast and the separation by climatic barriers would be omitted, then the method of Thiessen polygons is obtained.

2.2.3 Quantification of criteria selecting a set of stations

For other variables than rainfall a set of 1, 2, 3 or 4 stations is selected to be used for interpolation. The selection is done by computing for all such sets a 'suitability score'. The set with the lowest score is selected. The suitability score is defined by extending the difference score to sets of more than one point, whereas configuration criteria and a penalty for using one or two stations are added.

The importance of a surrounding configuration of a set of stations is taken into account by calculation of the distance from the location towards the centre of gravity of a given set. Annex 1.4 explains the effect of the configuration criterium in the case of three stations S_1, S_2, and S_3. For all sets possible with these three stations it shows the location of the centre of gravity (e.g. Z_{12}, is the centre of gravity of the set $S_1 + S_2$).

Around each centre of gravity a Thiessen polygon can be drawn. Discarding other criteria, the optimum configuration of stations for any location is indicated by the set of stations of the centre of gravity of the Thiessen polygon to which the location belongs.

For a set C of stations S_1, S_2, ..., S_n and location L the suitability score is defined as follows:

$$SSCORE_c = DIST_c + WALT*DALT_c + DIFCST_c + DCG_c + NSF_c*DSCORE_{\min} \qquad (2)$$

with:

$SSCORE_c$	:	the suitability score of the set C of stations S_1, S_2, ..., S_n in relation to location L (km);
$DIST_c$	:	the average distance between S_1, S_2, ..., S_n and L (km);
$DALT_c$	:	the average (absolute) difference in altitude between S_1, S_2, ..., S_n and L (m);
WALT	:	the weighting factor for DALT (km/m) (see (1));
$DIFCST_c$	:	the average (absolute) difference in (corrected) distance to the coast between S_1, S_2, ..., S_n and L (km) (see (1));
DCG_c	:	the distance between L and the centre of gravity of (S_1, S_2, ..., S_n) (km);
NSF	:	a factor that increases as the number of stations of the set of stations S_1, S_2, ..., S_n decreases; as a result the sets of more than two stations (NSF=0) are preferred compared to sets of two stations (NSF=0.2) or to a single station (NSF=0.5);
$DSCORE_{\min}$	:	the minimum difference-score of all of the calculated difference-scores of all available stations (km). This value characterizes the range of the other components of the formula; it balances the importance of the number of stations in relation to the other components.

According to the just mentioned definitions formula (2) can be written into more detail like:

$$SSCORE_c = \frac{1}{n}\sum_{i=1}^{n} DIST_i + WALT * \frac{1}{n}\sum_{i=1}^{n} |DALT_i| + \frac{1}{n}\sum_{i=1}^{n} |DIFCST_i| + \tag{3}$$

$$+ DCG_c + NSF_c * DSCORE_{min}$$

In order to save computer time the calculation of the suitability score is not carried out for all possible sets of 1, 2, 3 or 4 stations. In stead, for each location only the seven stations with the lowest DSCORE are used. This results in 98 sets for which the suitability score according to (3) is calculated. The set of stations with the minimum suitability score is considered as the optimum set of stations to be used for the estimation of the other weather data at location L.

Theoretically, it is possible that there is a set of stations with a lower suitability score than the one identified as the optimum set. Such a 'better than optimum' set would include one or more other stations than the seven stations with the lowest DSCORE. However it is unlikely for the configuration of the available stations within DBMETEO, which are quite evenly distributed. The probability would increase if seven or more stations are located close to each other in a cluster. In that case it might occur that due to low DSCORE's all seven of them are selected for the determination of the lowest suitability score, while because of a more advantageous configuration another station would have resulted in a lower suitability score.

Note that the occurrence of climatic barriers is not explicitly part of the calculation of the suitability score. Since it was already used for the computation of the difference score, no climatic barriers will occur anymore between the given location and the seven most similar stations.

2.2.4 Alternative selection procedures

During the iterative process of trying to identify the best selection algorithm, various alternatives were compared. The alternatives involved the use of a fixed number of 1, 2, 3 or 4 stations, or a variable number of 1-4 stations, selecting the stations by (combinations of) the criteria proximity, similarity in distance to the coast, and similarity in altitude. Moreover a penalty for sets with one or two stations could be incorporated.

The case of only one station means that the results of prediction are obtained by substituting the meteo data of one other station.
This station is selected as the most similar one. The similarity is defined in four alternative ways:
- as the nearest one (n.), the common Thiessen approach;
- as the nearest one corrected for differences in altitude (msa.);
- as the nearest one corrected for differences in distance from the coast (msc.);
- as the nearest one corrected for differences in altitude and distance from the coast (ms.).

The similarity definitions n., msa., msc., and ms. are effectuated by simpler versions of the calculation of the difference-score in (1).

2.3 Statistical validation of interpolation results

2.3.1 Comparison of alternative interpolation procedures for a reference station

The preceding Sections presented a procedure to select an optimum set of weather stations to estimate daily weather data for a given location. It is recalled that the estimation is made by means of averaging the data of the optimum set of stations without weighting for distance. The station values for temperature and humidity are adjusted for difference in elevation before averaging (see Section 2.2).

This Section describes the procedure followed to compare the interpolation results obtained with different sets of stations. The same procedure has also been used as a validation procedure to investigate whether the 'optimum set of stations' indeed offers the best estimates.

The interpolation procedures are compared on the basis of the prediction error, the difference between observed and interpolated values at a given reference location. Since no observations are available for the grid cells of 50 km x 50 km, these cells cannot be used as reference location. Therefore the comparison is made for a reference station. The procedure consists of two steps, firstly the estimation of daily weather data at the reference station using a specified method of selecting stations, and secondly a statistical evaluation of the interpolation results by comparing estimated with observed values. As a measure to quantify the precision of each interpolation method the mean root of the squared values of the prediction errors was used.

For the meteorological variables *radiation, sunshine duration, minimum temperature, maximum temperature, humidity, and windspeed, daily* values are predicted at a reference meteo station in the years *1975-1979*. This amounts to the prediction of 1826 daily values for every variable.

For the five years under consideration every day j the difference between the predicted value $x_{pred\ j}$ and the observed value $x_{obs\ j}$ is calculated for every meteorological variable.

If on a certain day for any of the meteorological variables a missing value occurs in the data to be used for interpolation, for all variables this day is left out in the evaluation of the interpolation method.

For the whole period of M days these differences between predicted and observed values are evaluated by calculation of the *Root Mean Squared Error* (RMSE), defined as:

$$RMSE = \sqrt{\frac{1}{M} * \sum_{j=1}^{M} (X_{obs_j} - X_{pred_j})^2} \tag{4}$$

with:

RMSE	:	Root Mean Squared Error
M	:	total number of days
$x_{obs\,j}$	:	observed value X at day j
$x_{pred\,j}$	:	predicted value X at day j
j	:	day number

Smaller values for this statistic indicate better prediction of a meteorological variable for a reference meteo station. The RMSE exaggerates the influence of large errors. Therefore it is a good indicator for the occurrence of outliers, complying to JRC's requirement to make realistic weather estimates for every day.

As a first example of constructing the basis for comparison may serve the application of the interpolation method 'average of 3 nearest stations' using Rouen as reference station (Table 1a). The table lists the seven most similar stations sorted on distance (DIST). Note that similarity in this case is restricted to proximity only (code P). The daily weather in Rouen is estimated by averaging the weather data of the set of the three nearest stations: Beauvais, Trappes and Abbeville. The root mean squared error over the whole period has been calculated for every variable (listed under abs). The results of nine days have been excluded because of missing values. The absolute values of the RMSE give an indication how well the algorithm performs. But it is more interesting to know how well this performance is in comparison with alternative procedures, and especially relative to the best possible procedure. The identification of the best possible procedure requires the testing of all theoretically possible alternatives and ranking of their results. For practical purposes the number of alternative station selections has been limited to 98 for each reference station,

The RMSE of each set is compared with the statistics of the other 97 sets, especially with the set that shows the lowest prediction error for that variable.

Division of the RMSE of each set by the RMSE of the best set gives the relative RMSE of each alternative station selection procedure. Table 1b gives the RMSE values of all sets. In this case the sets are ranked according to the suitability score of the proposed algorithm (1), so that its performance can be evaluated easily.

The selection algorithm works out perfectly, if the set that is selected by the algorithm is also the set that gives the lowest RMSE. The algorithm works out well if the prediction error of the selected set is not much larger than the lowest RMSE.

Table 1b gives an example for the reference station of Rouen. The Table lists the seven most similar stations calculated according to (1). The stations are sorted on their difference-score (see under DSCORE). The station of Beauvais has the lowest difference-score and will be used for the prediction of daily rainfall values of the reference station.

For the selection of the optimum set for interpolation the suitability score has been computed for all (98) different sets of at most four stations out of the seven stations (see under SSCORE). These sets are specified in a string of four positions (see under SET), with at each position the number (1 uptill 7) of a station; a zero at resp. the second, third or fourth position reflects a set of resp. one, two or three stations. E.g. in Table 1 set '1000', refers to the station of Beauvais and set '2367' refers to the stations of Trappes, Chartres, Paris and Caen. For all these sets out of seven stations the suitability scores are determined according to (3). The sets are sorted on their suitability score.

Table 1 gives the results of the 30 sets with the lowest suitability scores, and in addition, the results of the 7 sets representing the single stations.

Thus the set '1450' (Beauvais, Alencon, Abbeville) has been selected for the interpolation.

For a given reference station the mentioned 98 sets are sorted according to the RMSE of every variable. The lowest RMSE of all 98 sets is considered to reflect the best possible prediction for a variable to be found at all.

For every set a *relative RMSE per variable* (see under rel) is calculated by division of the absolute RMSE (see under abs) with the lowest RMSE of all 98 sets. The relative RMSE is an indicator for the accuracy of the prediction of a set in comparison to the best possible prediction of all sets: a value of 1.00 [rmse rmse^{-1}] indicates the optimum prediction, a value of e.g. 1.15 [rmse rmse^{-1}] indicates an increase of prediction error of 15%. In Table 1b the best possible prediction for minimum as well as maximum temperature is found using set '1257'.

In addition to the variable-specific relative RMSE's, an *average relative RMSE* (see under AVE) of every set is calculated as the average of the relative RMSE's of the variables radiation, sunshine duration, minimum temperature, and maximum temperature. These variables are selected because they are the most important input data for crop growth modelling and display more variation than the variables windspeed and vapour pressure.

Note however that radiation and sunshine duration are strongly correlated as the used radiation is calculated on the basis of sunshine duration. To some extent, the minimum and maximum temperature are correlated as well. In Chapter 3 the differences in performance between the variables will be investigated.

An average relative RMSE of e.g. 1.20 [rmse rmse^{-1}] indicates that for the set the prediction error of the combined prediction of the variables radiation, sunshine duration, minimum temperature, and maximum temperature is on average 20% larger than the errors of the best possible prediction for the separate variables. These optimum predictions are not necessarily given by the same set. Therefore an average relative RMSE of 1.00 [rmse $rmse^{-1}$] does not have to exist.

The sets are ranked according to their average relative RMSE's, the set with number one having the lowest average relative RMSE. E.g. in Table 1b the set with rank number 1 (see under rnk) corresponds with an average relative RMSE of 1.01 [rmse $rmse^{-1}$] (see under AVE rel).

Table 1 Example of reference station statistics: Rouen

1a

Reference Station: Rouen
WMONR: 7037; LAT.: 49.4; LON.: 1.2; ALT.: 157.0; DCOAST: 58.8
7 Most similar stations:

NR	NAME	WMONR	LAT	LONG	ALT	DCOAST	DIST	DSCORE
1	Beauvais	7055	49.5	2.1	109.0	82.8	68.8	68.8
2	Trappes	7145	48.8	2.0	168.0	143.6	91.4	91.4
3	Abbeville	7005	50.1	1.8	74.0	21.0	95.7	95.7
4	Paris/Le Bou	7150	49.0	2.5	66.0	142.2	103.1	103.1
5	Chartres	7143	48.5	1.5	155.0	142.6	104.3	104.3
6	Caen	7027	49.2	-0.4	78.0	13.0	120.4	120.4
7	Alencon	7139	48.5	0.1	144.0	92.7	130.2	130.2

Combination with 3 most similar p station(s):

Station	<------RMSE													------>	IDMIS
	RAD		SSD		TMN		TMX		AVE	VAP		WIN			
	abs	rel	abs	rel	abs	rel	abs	rel	rel	abs	rel	abs	rel		
7037	1613	1.14	1.44	1.11	1.06	1.05	0.86	1.05	1.09	0.06	1.17	0.80	1.07		9

1b

Reference Station: Rouen
WMONR: 7037; LAT.: 49.4; LON.: 1.2; ALT.: 157.0; DCOAST: 58.8
7 Most similar stations:

NR	NAME	WMONR	LAT	LONG	ALT	DCOAST	DIST	DSCORE
1	Beauvais	7055	49.5	2.1	109.0	82.8	68.8	104.8
2	Trappes	7145	48.8	2.0	168.0	143.6	91.4	128.4
3	Chartres	7143	48.5	1.5	155.0	142.6	104.3	136.5
4	Alencon	7139	48.5	0.1	144.0	92.7	130.2	153.7
5	Abbeville	7005	50.1	1.8	74.0	21.0	95.7	170.6
6	Paris/Le Bou	7150	49.0	2.5	66.0	142.2	103.1	179.7
7	Caen	7027	49.2	-0.4	78.0	13.0	120.4	201.4

Selected set for reference station 7037 is 1450

30 Sets with the lowest scores:

Nr	set	sscore	<------RMSE														------>	IDMIS
			RAD		SSD		TMN		TMX		AVE		VAP		WIN			
			abs	rel	abs	rel	abs	rel	abs	rel	rel	rnk	abs	rel	abs	rel		
1	1450	155.9	1522	1.07	1.36	1.05	1.11	1.09	0.84	1.03	1.06	4	0.06	1.10	0.84	1.12		49
2	1357	162.7	1417	1.00	1.30	1.00	1.03	1.02	0.82	1.01	1.01	1	0.05	1.00	0.78	1.04		126
3	1257	165.7	1456	1.03	1.31	1.00	1.01	1.00	0.81	1.00	1.01	2	0.05	1.07	0.77	1.03		12
4	2570	166.8	1588	1.12	1.43	1.09	1.07	1.06	0.93	1.14	1.10	11	0.06	1.16	0.83	1.11		8
5	1245	170.7	1550	1.09	1.38	1.06	1.03	1.01	0.88	1.08	1.06	5	0.06	1.10	0.92	1.24		54

Continuation Table 1b

Nr	set	sscore	RAD abs	RAD rel	SSD abs	SSD rel	TMN abs	TMN rel	TMX abs	TMX rel	AVE rel	AVE rnk	VAP abs	VAP rel	WIN abs	WIN rel	IDMIS
6	1270	171.7	1578	1.11	1.41	1.09	1.07	1.06	0.94	1.16	1.10	13	0.06	1.16	0.84	1.13	12
7	1345	173.2	1530	1.08	1.39	1.07	1.09	1.08	0.94	1.15	1.09	9	0.05	1.06	0.81	1.09	168
8	1457	179.5	1528	1.08	1.37	1.05	1.09	1.08	0.89	1.10	1.08	7	0.06	1.13	0.76	1.02	49
9	2450	181.9	1700	1.20	1.51	1.16	1.05	1.04	0.97	1.19	1.15	22	0.06	1.19	1.02	1.37	50
10	1570	182.7	1534	1.08	1.38	1.06	1.13	1.12	0.94	1.16	1.10	12	0.06	1.13	0.89	1.19	7
11	5670	183.9	1606	1.13	1.44	1.11	1.12	1.10	0.95	1.17	1.13	19	0.06	1.15	0.86	1.16	8
12	1350	184.0	1537	1.08	1.40	1.07	1.11	1.09	0.85	1.05	1.08	6	0.06	1.11	0.75	1.00	123
13	1240	185.4	1789	1.26	1.59	1.22	1.17	1.15	1.20	1.48	1.28	53	0.06	1.26	1.24	1.66	54
14	1670	185.8	1595	1.12	1.43	1.10	1.17	1.15	1.02	1.25	1.16	26	0.06	1.18	0.83	1.11	12
15	2357	186.4	1589	1.12	1.45	1.11	1.06	1.05	0.91	1.12	1.10	10	0.05	1.07	0.77	1.04	127
16	1370	186.4	1580	1.11	1.44	1.11	1.12	1.10	1.00	1.23	1.14	20	0.06	1.11	0.81	1.08	126
17	1567	187.3	1485	1.05	1.34	1.03	1.09	1.08	0.86	1.05	1.05	3	0.05	1.09	0.79	1.05	12
18	1456	187.4	1566	1.10	1.40	1.07	1.13	1.11	0.95	1.17	1.12	17	0.06	1.12	0.87	1.17	49
19	1235	188.8	1616	1.14	1.47	1.13	1.08	1.06	0.92	1.13	1.11	16	0.06	1.12	0.78	1.05	128
20	1237	189.0	1659	1.17	1.50	1.15	1.10	1.09	1.03	1.26	1.17	28	0.06	1.13	0.82	1.10	131
21	3570	189.9	1585	1.12	1.46	1.12	1.09	1.08	0.93	1.15	1.12	18	0.05	1.09	0.88	1.18	122
22	1250	193.9	1613	1.14	1.44	1.11	1.06	1.05	0.86	1.05	1.09	8	0.06	1.17	0.80	1.08	9
23	3450	194.1	1725	1.22	1.56	1.20	1.14	1.12	1.08	1.32	1.22	39	0.06	1.16	0.88	1.18	164
24	1267	194.2	1669	1.18	1.49	1.15	1.13	1.11	1.04	1.28	1.18	31	0.06	1.21	0.86	1.16	17
25	2567	194.2	1607	1.13	1.44	1.11	1.07	1.06	0.92	1.13	1.11	14	0.06	1.13	0.80	1.07	13
26	1247	196.0	1686	1.19	1.50	1.15	1.11	1.10	1.08	1.33	1.19	36	0.06	1.21	0.95	1.27	54
27	3567	196.4	1569	1.11	1.43	1.10	1.08	1.07	0.94	1.16	1.11	15	0.05	1.07	0.78	1.05	127
28	2345	196.6	1756	1.24	1.58	1.22	1.11	1.09	1.09	1.34	1.22	42	0.06	1.16	0.95	1.28	169
29	1340	196.7	1817	1.28	1.64	1.26	1.27	1.25	1.29	1.59	1.35	62	0.06	1.25	1.07	1.43	168
30	1230	197.2	1918	1.35	1.73	1.33	1.23	1.21	1.21	1.48	1.34	60	0.07	1.32	0.99	1.32	128
Sets with only one station:																	
1	1000	226.0	1846	1.30	1.66	1.27	1.44	1.42	1.09	1.34	1.33	57	0.08	1.49	0.91	1.21	4
43	2000	272.2	2411	1.70	2.14	1.64	1.53	1.51	1.43	1.77	1.66	91	0.09	1.69	1.48	1.99	5
69	3000	293.2	2601	1.84	2.31	1.78	1.58	1.56	1.66	2.05	1.80	95	0.09	1.78	1.12	1.50	119
84	4000	336.3	2732	1.93	2.41	1.85	1.80	1.77	2.11	2.60	2.04	98	0.10	2.02	1.86	2.49	45
92	5000	318.6	2359	1.66	2.07	1.59	1.45	1.43	1.44	1.78	2.62	87	0.08	1.57	1.29	1.73	0
96	6000	335.2	2526	1.78	2.24	1.72	1.65	1.63	1.73	2.13	2.82	96	0.10	1.95	1.25	1.68	5
98	7000	374.2	2658	1.88	2.39	1.84	1.73	1.71	1.95	2.39	2.95	97	0.10	1.98	1.36	1.83	3

Description of acronyms in tables 1a and 1b:

WMONR : station number of the World Meteorological Organisation
LAT : latitude of the station (decimal degrees)
LON : longitude of the station (decimal degrees)
ALT : altitude of the station (m)
DCOAST : distance to the coast (km)
DIST : distance from a station to the reference station (km)
DSCORE : difference-score between a station and the reference station (km)
SET : a set of stations
NR : number of a set of stations, the numbers increasing with the suitability score
SSCORE : suitability score of a set of stations for a reference station (km)
RMSE : root mean squared error in the unit of that variable or as a [rmse RMSE-1]
RAD : radiation (kJ)
SSD : sunshine duration (hrs)
TMN : minimum temperature (°C)
TMX : maximum temperature (°C)

AVE	**: average relative RMSE of RAD, SSD, TMN, and TMX ([rmse rmse^{-1}])**
VAP	**: vapour pressure (kPa)**
WIN	**: windspeed (m/s)**
abs	**: absolute RMSE of a variable, in the unit of that variable**
rel	**: relative RMSE of a variable ([rmse rmse^{-1}])**
rnk	**: ranking of a set increasing with AVE (-)**
IDMIS	**: number of missing days not used to calculate the RMSE**

The selection algorithm could be considered to perform well if the increase in suitability score (see Table 1b, under SSCORE) corresponds with an increase in the average relative RMSE. For Table 1b the algorithm will select set nr 1 (stations number 1, 4 and 5) because it has the lowest suitability score (optimum set). This set shows a good average relative RMSE (1.06 [rmse rmse^{-1}]) and ranking (number 4). The algorithm will identify the best possible set, i.e. the set with the lowest relative average RMSE, as the second one to be selected. This is set '1357' which has an average relative RMSE of 1.01 [rmse rmse^{-1}] and of course rank number 1.

The three stations of the example in Table 1a Beauvais, Trappes and Abbeville, are ranked as number 1, 2, and 5 on the basis of the DSCORE. The results of Table 1a can be found in Table 1b for station set 1250 on the 22nd line. This set shows an average relative RMSE of 1.09 [rmse rmse^{-1}] and is ranked as the 8th best performer.

2.3.2 Comparison of alternative interpolation procedures for regions

In order to compare the successive alternative interpolation procedures defined during the development process, several reference stations were grouped into test regions. For such specified groups of reference stations *regional means of the average relative RMSE* are calculated. These means serve to identify regional differences in the performance of the interpolation procedures.

In this next level of comparison the 97 other station selections are no longer considered, and in stead the comparison is focussed on alternative ways of selecting the 'optimum set' and of weighting for distance.

As basis for the comparison serves always the best performing set among the 98 investigated for each reference station, with interpolation by averaging without weighting for distance. The results of the comparison are expressed by the average relative RMSE. In this way the comparison procedure offers the possibility to investigate how well the various alternatives perform over regions.

Initially, during the iterative development and validation process, test regions were defined, comprising a number of test regions. For example Northern Germany and the Netherlands to evaluate the coastal effect, Southern Germany to evaluate the effect of altitude, and Spain to evaluate both effects. The algorithm was then applied to test regions within France and refined further. Application of the algorithm to the United Kingdom and Ireland did not indicate a need for further refinement. It was then decided to apply the algorithm to as much as possible meteo stations of the DBMETEO database for comparison of the alternative interpolation procedures.

Due to a considerable amount of missing data in the period 1975-1979 (mainly sunshine duration) some (mostly Spanish) stations are excluded from the comparison. The Greek stations are excluded because of the monthly character of the data. The Italian data were not available at that time.

A total number of 233 meteo stations of the United Kingdom, Ireland, Denmark, The Netherlands, Belgium, France, Spain, Portugal, and Germany and 18 meteo stations in some bordering areas in Switzerland, Austria and Slovenia were used as reference stations. The comparisons were then made for all 233 stations together, and countrywise.

Afterwards 24 Italian stations were used as an independent data set to validate the developed procedure.

Figure 2 shows the location of all of these 275 stations.

Although the worst stations were already excluded, omissions of up to 60% of the period were found in the interpolation results. Due to the occurrence of missing values this was found in some of the remaining reference stations in Spain and Italy.

To develop and compare the proposed algorithms the program VALMET was developed. VALMET offers various alternatives to estimate weather variables with the use of a fixed number of 1, 2, 3 or 4 stations, or a variable number of 1-4 stations, selecting the stations by (combinations of) the criteria proximity, and similarity in distance to the coast, and in altitude. It is also possible to incorporate a penalty for sets of stations with one or two stations. Annex 2 describes VALMET into more detail. It also describes the program REGVAL (REGionalize VALidation) to deduce specific regional results.

3 Results

This Chapter describes the results of the proposed algorithm for the selection of an optimum set of stations, and subsequent interpolation method between the meteo data of the selected stations. These results are discussed by comparing them with the results of the statistically best performing set of stations in terms of RMSE. In addition, the results obtained with alternative selection and weighting procedures will be included in the comparison. The results can be divided into *selected sets of stations per reference station* (3.1) and *regional results on the basis of mean relative RMSE* (3.2).

The whole EC, except Italy and Greece, including bordering regions in Switzerland, Austria and Slovenia was used to compare alternatives and develop the proposed algorithm. In order to validate the comparisons and the final choice of the selection method the computations were repeated on an independent set of stations, i.e. the stations in Italy. For practical reasons the results of the stations used for the development of the algorithm, and the results of the (Italian) stations that were used for the validation of the algorithm are presented in the same Tables and Figures.

The proposed algorithm for the selection of a set of stations and the interpolation was developed in a stepwise procedure on the basis of a limited number of tests with a small number of reference stations.

The criteria of the algorithm are re-evaluated in 3.1 by a further investigation on 275 stations. In 3.1.1 the existence of climatic barriers is presented. Section 3.1.2 summarizes the number of stations in the selected sets. Differences between best performing sets and selected sets of stations are investigated more into detail in Section 3.1.3.

As described in Chapter 2 the regional means of the average relative RMSE of specified validation regions have been determined (3.2). In 3.2.1 the results of alternative station selection procedures are arranged by number of stations ranging from 1 to 4. For each given number of stations, various criteria for the selection of stations have been applied, based on different definitions of station similarity. Finally the results of the proposed algorithm, selecting a variable number of 1 to 4 stations on the basis of the configuration of the stations according to (2), is given.

For comparison the effect of a refinement of the procedure is demonstrated with the results obtained through interpolation with additional weighting for distance in the cases of four or a variable number of stations (Section 3.2.2).

In Chapter 2 the average relative RMSE was introduced as an overall criterion to validate the interpolation algorithms. To check the assumption that this averaged value can represent all meteorological variables, in 3.2.3 variable specific results are given as well.

Next 3.2.4 contains country specific results to distinguish possible 'country effects'.

3.1 Selected sets of stations per reference station

For all (275) reference stations that have been used Annex 3 contains the results of the selection algorithm for the individual stations. It consists of 275 tables with the same format as Table 1b. The two most prominent cases of station selection are visualized on the maps of Annexes 4 and 5, namely the statistically best performing station network, and the station network selected by the algorithm as 'optimum'. For practical reasons the whole area of the EC is split into 6 maps with zones covering respectively United Kingdom and Ireland (Annex .1), Denmark, the Netherlands, Belgium and Germany (.2), France (.3), Portugal and Spain (.4), Italy (.5), and the Alps and surrounding area (.6).

The maps of Annex 4 show for all reference stations the statistically best performing set of stations that was found among the mentioned 98 alternative sets (Section 2.5): the (from-to) direction of the arrows between two stations indicate that a station is used to predict the meteo data of the other one. The arrows are all curved clockwise in the from-to direction. Figure 4 shows an example of the representation of neighbouring stations A, B, and C used to estimate daily meteorological data of reference station R.

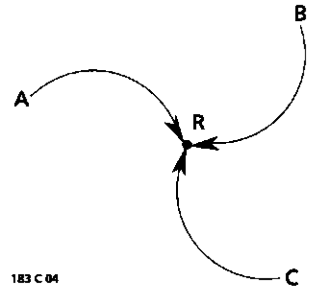


Fig. 4 Representation of neighbouring stations A, B, and C used to estimate daily meteorological data of reference station R

For the example of Table 1b one can recognize arrows to 7037 from 7027, 7005, 7055, and 7143.

Annex 6 shows for all reference stations the absolute RMSE's for all meteorological variables, that result from the statistically best performing set of stations with the lowest prediction error for that variable. In most cases the lowest prediction errors can be found in the Tables of Annex 3. Sometimes, however this value is not among the first 30 sets of the algorithm.

Therefore the lowest absolute RMSE's have been recalculated with the use of the rounded data from Annex 3. This explains the differences between some values in Annexes 3 and 6. For example, the lowest radiation RMSE for Rouen has an original value of 1417. (Annex 3), but has been recalculated (dividing 1522. with 1.07) as 1422. (Annex 6).

From Annex 6 it can be seen that the absolute values of the RMSE's per weather variable are highest in Southern Europe and in mountainous regions. The highest RMSE's for radiation, sunshine duration, minimum temperature, maximium temperature, vapour pressure or windspeed can be found for respectively Passau (4177. kJ), Passau (3.64 hrs), Olbia/Costa (4.47 °C), Olbia/Costa (7.12 °C), Guadalajara and Tarifa (0.26 kPa), and Tarifa (5.62 m/s). The lowest RMSE's for radiation, sunshine duration, minimum temperature, maximium temperature, vapour pressure or windspeed can be found for respectively Zuid Limburg (1109. kJ), Zuid Limburg (0.98 hrs), Lubeck and Lingen (0.71 °C), Birr (0.61 °C), Birr and Mullingar (0.03 kPa), and Schwerin (0.44 m/s).

In the maps of Annex 5 the sets of stations as selected by the algorithm are shown in the same way as in Annex 4. Ideally the maps of Annex 5 should show the same arrow-structure as the maps of Annex 4. In the tables of Annex 3 can be found that a slightly different arrow-structure might be almost just as good as the best one.

In the maps of Annex 4 the best possible configuration between stations is presented. Two clear networks of stations selecting each other can be identified. There appears to be a clear *network of coastal stations* selecting each other, as well as a *network of high-altitude stations*. The last network is most striking in the Spanish highland. Furthermore the existence of *climatic barriers* around the Pyrenees and the Alps (Section 3.1.1) can be seen.

The maps of Annex 5 show the network of stations generated by the proposed algorithm. Because the algorithm doesn't take into account all local effects, the maps of Annex 5 show a more regular pattern. But in general the patterns between the maps of Annexes 4 and 5 are quite similar. The climatic barriers around the Pyrenees and the Alps, as well as the network of coastal stations and the network of high-altitude stations can be clearly recognized too.

3.1.1 Climatic barriers

Before a climatic barrier was included the results of the best performing set of stations on the map of Annex 4.4 showed the absence of arrows between stations on both sides of the Pyrenees. This indicated the existence of a climatic barrier. All reference station results of stations near to the Pyrenees were investigated in detail. Table 2 shows the results of the reference station of Huesca in Spain. In the first part of the Table no climatic barrier was in the selection algorithm.

It appears that the RMSE of French stations is much higher than the RMSE of the Spanish stations. The result holds if sets of stations are used. Similar results were found at other stations close to the Pyrenees. All French stations with poor results on Spanish stations and Spanish stations with poor results on French stations have received climatic codes (resp. -1 and 1). To improve the results the algorithm checks the values of a climatic code, to recognize stations to be on opposite sides of climatic barriers. If this is the case, the stations disqualify each other from the selections (see formula 1).

Table 2 Results for reference station Huesca, Pyrenees (WMO-number 8094)

No climatic barrier				
Combinations with only one station:				
NR	**WMONR**	**NAME**	**rel. RMSE [rmse rmse^{-1}]**	**RNK**
1	**8085**	**Pamplona/Noa**	**1.74**	**78**
2	**7621**	**Tarbes**	**2.23**	**95**
3	**8160**	**Zaragoza A.**	**1.02**	**2**
4	**7627**	**Saint-Girons**	**2.25**	**97**
5	**8157**	**Daroca O.**	**1.30**	**25**
6	**7610**	**Pau**	**2.31**	**98**
7	**8233**	**Calamocha**	**1.48**	**50**
Selected combination 2345:				
2345			**1.38**	**37**
Climatic barrier included:				
1	**8085**	**Pamplona/Noa**	**1.80**	**98**
2	**8160**	**Zaragoza A.**	**1.06**	**7**
3	**8157**	**Daroca O.**	**1.36**	**79**
4	**8233**	**Calamocha**	**1.54**	**96**
5	**8266**	**Guadalajara**	**1.52**	**94**
6	**8221**	**Madrid/Baraj**	**1.58**	**97**
7	**8235**	**Teruel**	**1.54**	**95**
Selected combination 123:				
123			**1.13**	**24**

From Annex 5.4 it can be seen that the algorithm indeed does not allow any station selections crossing the Pyrenees.

In a similar way, a climatic barrier was detected around the Alps. Weather stations at opposite sides of the Alps were given climatic codes of 2 (south) or -2 (north).

Annex 7 gives an overview of all weather stations involved in these climatic barriers, i.e. stations with non-zero climatic codes.

3.1.2 Number of stations in the selected sets

The statistically best performing set of stations contains usually three or four stations, and rarely only one station. For most reference stations the number of stations in the best performing set and in the set selected by the algorithm are given in Table 3.

Table 3 The number of reference stations with the statistically best performing sets, and with the sets selected by the algorithm, using 1, 2, 3 or 4 stations

	number of reference stations	
	with best performing sets	with sets selected by the algorithm
sets using 1 station	5	23
sets using 2 stations	51	57
sets using 3 stations	96	140
sets using 4 stations	103	55
	255	275

For 20 reference stations the exact number of stations in the best performing sets is not known, because it is not listed in the first 30 lines of Annex 3. However, from the last 6 lines (with the results with only one station), it can be concluded that they use more than one station.

If the use of only one station yields the best estimate, this concerns mostly stations at very short distance from each other. The five cases can be seen on the maps in Annex 4. The weather at Roches Point (3592) is best estimated by substitution with Cork A (3955), Bale-Mulhouse (7299) can be best replaced by Basel (6998), Tarifa (8485) by San Fernando (8453), and Portoroz (13105) by Trieste (16110). However, the reverse is not true, because other stations or sets of stations may give better results.

A special case forms the substitution of Aurillac (7549) by Gourdon (7535), not really close to each other.

From Table 3 it can be seen that the number of stations per set is in general higher in the best performing sets than in the sets selected by the proposed algorithm: In the case of sets with 4 stations, there exists at least 103 best performing sets versus only 55 sets selected by the algorithm.

3.1.3 Differences between best performing sets and selected sets of stations

An ideal algorithm would select the best performing set indicated as rank 1 in Table 1b. The proposed algorithm selects for 61 reference stations the highest ranked set. The rankings of all selected sets are given in Table 4.

Table 4 Ranking of the sets of stations selected by the algorithm for the 275 reference stations

rank of the selected set	**number of reference stations**
1	**61**
2	**36**
3	**19**
4	**12**
5	**7**
6-10	**39**
11-20	**39**
21-30	**19**
31-40	**12**
41-50	**7**
51-60	**9**
61-70	**7**
71-80	**3**
81-90	**5**
91-98	**0**

	275

It shows that more than 60% of the selected sets are among the 10% best performing sets (174 sets with a ranking <= 10). Almost 10% of the selected sets are among the 50% worst performing sets (24 sets with a ranking > 50).

The reference stations for which the algorithm did not give good performing sets of stations can be traced back in Annex 3. It is difficult to detect the reason of the anomaly, or to define general rules to identify better sets of stations. The reference stations for which the station selection with the algorithm was less successful are concentrated in a few regions:

- Southern Germany, Austria and Slovenia: Passau (10893), Regensburg (10776), Nordlingen (10991), Salzburg (11150), Reigersberg (11236), Lienz (11204), Villacher A. (11212), Vedrijan (13993), Golnik (13991), and Lublijana (13015).
- France around the Central Massif: especially Le Puy (7471) and Millau (7558), and Bastia (7790) on Corsica.
- Spain, some stations in the interior: Cuenca (8231), Soria (8148), Badajoz (8330), Ciudad Real (8348), Pamplona (8085), Valladolid (8141), Leon (8055) and Navacerrada (8215).
- Italy, some coastal stations: Messina (16420), Crotone (16350) and Genova (16120).
- Italy, Campobasso (16252) and Torino (16059).
- North West Europe: Kilkenny (Ireland; 3960), Munster (Germany; 10315) and Zuid Limburg (The Netherlands; 6380).

Apart from differences in relative performance of the algorithm over regions, differences in absolute performance exist (Section 3.1). From Annex 6 it can be seen that from the just mentioned stations especially Munster and Zuid Limburg have very low absolute RMSE's in their best possible sets. This makes the gap between the lowest prediction errors and the RMSE's of the selected set higher than for other stations.

3.2 Regional results

3.2.1 Alternative selection procedures

Various selection algorithms were compared. The alternatives involved the use of a fixed number of 1, 2, 3 or 4 stations, or a variable number of 1-4 stations, selecting the stations by (combinations of) the criteria proximity, and similarity in distance to the coast and in altitude. Moreover a penalty for sets with one or two stations could be incorporated. The influence of the number of stations and the selection criteria on the interpolation are shown in Table 5.

Table 5 Overview of the mean relative performance [rmse rmse^{-1}] of several interpolation algorithms as compared to the best possible prediction, within the specified region (of 233 reference stations in the EC)

		selection criteria			
number of stations		**proximity**	**proximity coast**	**proximity altitude**	**proximity coast altitude**
fixed	**1**	**1.45**	**1.46**	**1.43**	**1.42**
fixed	**2**	**1.25**	**1.23**	**1.21**	**1.21**
fixed	**3**	**1.20**	**1.17**	**1.18**	**1.16**
fixed	**4**	**1.18**	**1.16**	**1.16**	**1.15**
variable	**1-4a**	**1.19**	**1.20**	**1.17**	**1.17**
variable	**1-4b**	**1.15**	**1.15**	**1.13**	**1.12**

1-4a: variable at most 4 stations, without penalty score for sets with 1 or 2 stations
1-4b: variable at most 4 stations, with penalty score for sets with 1 or 2 stations

To show the influence of the number of stations and the selection criteria on the interpolation the results of Table 5 are also shown as a graph (Figure 5).

From Figure 5 it can be concluded that the performance of the algorithm improves most if the *number of stations* to be used in the interpolations is increased. Regardless of the involved similarity criteria, increasing the number of stations from 1 to 2 shows the largest improvement (at least 20%). From 2 to 3 stations the improvement is still around 4%, from 3 to 4 stations there's almost no improvement (1-2% for the whole area) anymore. From this it can be concluded that the use of more than 4 stations can be safely excluded.

If the number of stations is variable as a function of configuration, it appears that a fixed number of 4 stations is better. But if the criterion of the algorithm with a variable number of stations is extended with a penalty for sets with two stations and an even stronger penalty for sets with only one station, a better performance is found (around 3% better than with a fixed number of stations).

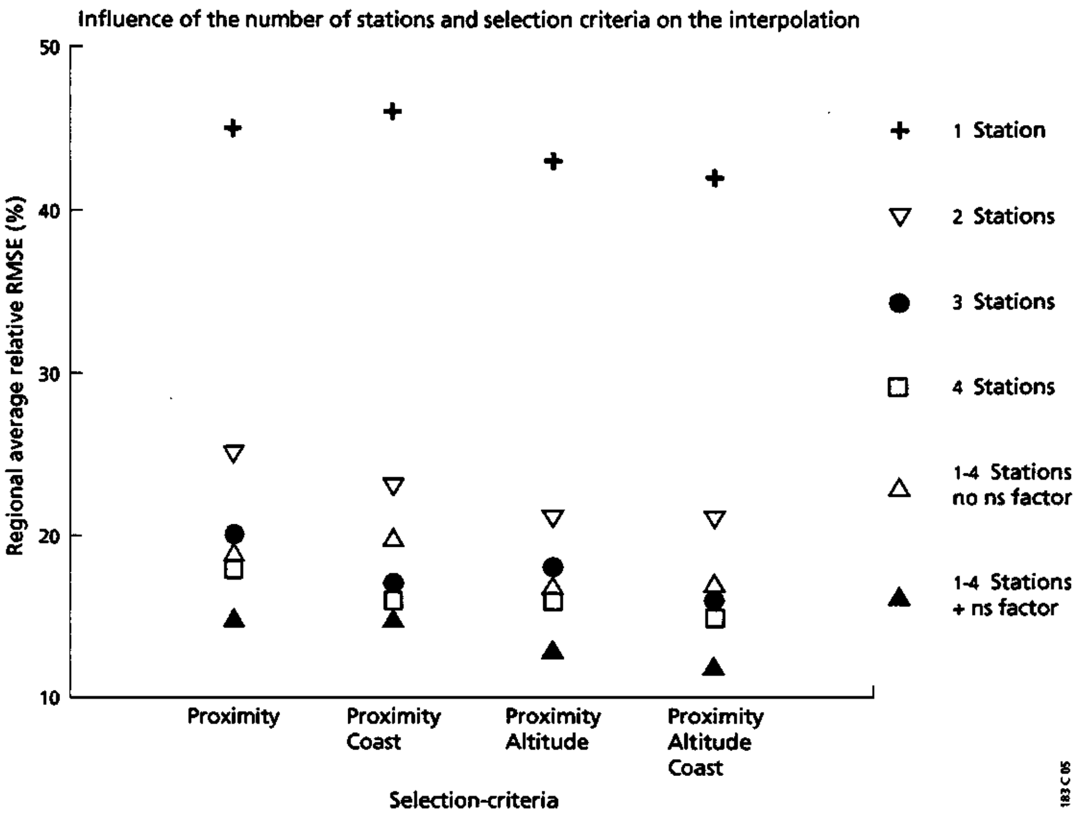


Fig. 5 Influence of the number of stations and selection criteria on the interpolation

From Figure 5 follows that defining *similarity* as a combination of proximity, altitude and distance to the coast always leads to some improvement in comparison with criteria based on proximity or on combinations of proximity and coast, or proximity and altitude (1-3%). Extending the proximity criterion with the altitude-criterion always improves the performance. Extending the proximity criterium only with the coast-criterium does not improve the performance. The coast-criterium only has a positive effect on the performance in combination with the altitude-criterion.

In general it appears that the selection algorithm for interpolation should take into account the use of a variable number of (1-4) stations, selection of stations as a function of proximity, altitude and distance to the coast, and a surrounding configuration of stations with a preference for the use of more than 2 stations. This confirms the proposed algorithm formulated in (3).

3.2.2 Interpolation when weighting for distance

So far all stations are assumed to be of equal importance and no weighting for distance is applied.

Finally for interpolation between the two, three or four most similar stations and for interpolation according to the proposed interpolation method, Table 6 gives the results if the influence of the stations is inversely weighted for distance according to (9), with various weighting powers p.

$$V_{est} = \frac{1}{\sum_{i=1}^{n} \left(\frac{1}{D_i^p}\right)} * \sum_{i=1}^{n} \left(\frac{V_i}{D_i^p}\right) \tag{5}$$

Table 6 Overview of the mean relative performance [rmse rmse⁻¹] of several interpolation algorithms with weighting for distance as compared to the best possible prediction, within the specified region of 233 reference stations in the EC

		<-----weighting power p----->				
		0.0	**0.5**	**1.0**	**1.5**	**2.0**
number	**2 msw.**	**1.21**	**1.21**	**1.21**	**1.21**	**1.22**
of	**3 msw.**	**1.16**	**1.15**	**1.15**	**1.15**	**1.16**
stations	**4 msw.**	**1.15**	**1.13**	**1.12**	**1.12**	**1.14**
	1-4 msw.	**1.12**	**1.16**	**1.16**	**1.17**	**1.18**

msw.: nearest, most similar in altitude and distance to the coast, penalty for few stations included, weighted inversely for distance with weighting power p

Note that the use of a weighting power of zero corresponds with the proposed algorithm of averaging without weighting.

From Table 6 it can be seen that inversely *weighting for distance* improves the performance for a fixed number of 4 stations with 3%. There is not much difference between the RMSE's with different weighting powers. If the number of stations is fixed the optimum weighting power is around 1.0-1.5 in all cases.

But if the proposed algorithm with a variable number of stations is weighted inversely for distance, it shows a worse performance (4% worse).

Inverse weighting for distance using always 4 stations shows the same performance as unweighted interpolation according to the proposed algorithm (a relative RMSE of 1.12 [rmse $rmse^{-1}$]).

It appears that the influence of the distance is already incorporated optimally within the proposed unweighted algorithm. Chapter 5 discusses the preference for an algorithm with a variable number of stations in comparison to an algorithm with a fixed number of (4) stations.

3.2.3 Differences between meteorological variables

In Chapter 2 the average relative RMSE is introduced as an overall criterion to validate the interpolation algorithm. The performance of the various interpolation algorithms is evaluated with the help of the mean value of the relative RMSE of the variables radiation, sunshine duration, minimum temperature and maximum temperature. These variables are selected because they are the most important input data for crop growth modelling and are expected to display more variation than the other variables windspeed and vapour pressure.

To investigate the differences in performance between the variables, the variable specific mean relative performance of several interpolation algorithms of the specified region of 233 reference stations in the EC is determined. The results are summarized in Table 7.

Table 7 Overview of the mean relative performance [rmse $rmse^{-1}$] of several interpolation algorithms as compared to the best possible prediction, within the specified region of 233 reference stations in the EC of the individual meteorological variables radiation (rad), sunshine duration (ssd), minimum temperature (tmn), maximum temperature (tmx), vapour pressure (vap), and windspeed (win)

		<-----------------meteorological variable----------------------------->					
		rad	**ssd**	**tmn**	**tmx**	**vap**	**win**
number of	**1 ms.**	**1.37**	**1.35**	**1.50**	**1.47**	**1.44**	**1.59**
stations	**2 ms.**	**1.18**	**1.17**	**1.28**	**1.25**	**1.23**	**1.38**
	3 ms.	**1.14**	**1.13**	**1.22**	**1.21**	**1.18**	**1.30**
	4 ms.	**1.13**	**1.11**	**1.20**	**1.19**	**1.15**	**1.26**
	1-4 ms.	**1.07**	**1.06**	**1.21**	**1.16**	**1.15**	**1.32**
ms.	**nearest, most similar in altitude and distance to the coast, number of stations factor included, no weighting**						

From Table 7 the *variable specific differences* can be deduced. It appears that regardless of the number of stations to be used, the meteorological variables can be divided into three groups:

1 radiation and sunshine duration; since radiation is calculated on the the basis of the sunshine duration, this seems obvious. This group shows the best performance (relative RMSE's of 1.06-1.07 [rmse $rmse^{-1}$] for the proposed algorithm).
2 minimum temperature, maximum temperature and vapour pressure; It is obvious that minimum and maximum temperature are strongly correlated. The correlation between temperature and vapour pressure can be explained physically as well. For the proposed algorithm the relative RMSE's are 1.21, 1.16 and 1.15 [rmse $rmse^{-1}$] respectively.
3 windspeed; Windspeed shows clearly a much worse performance than the other variables (1.32 [rmse $rmse^{-1}$] for the proposed algorithm).

The average value based on the relative RMSE's of the variables radiation, sunshine duration, minimum temperature and maximum temperature gives a good balance between group 1 and 2. Since windspeed is less important for the crop growth model, it is not considered a problem that the worse RMSE of the windspeed is excluded from the average. The use of the proposed average relative RMSE appears to be a proper criterion to compare the interpolation algorithms.

3.2.4 Differences between countries

The proposed algorithm is developed on the reference stations of most of the EC-countries and some bordering countries. In order to validate the comparisons the computations were repeated on the stations in Italy.

Annex 8 gives an overview of the median values (med), the mean values (ave), and the standard deviation (std) per country of the lowest absolute RMSE's per variable. These lowest absolute RMSE's can be considered as a measure for the precision of interpolation that can be achieved within the framework of this study.

Low values of the standard deviation point to countries that behave climatologically more uniform.

This can be seen most clearly in Belgium, with an exception for maximum temperature. High values indicate more climatological difference within a country, which is most obvious for Spain. The median values have been calculated next to the average values to investigate whether the average values are strongly dominated by the extreme values. In most cases Annex 8 shows a bit smaller value for the medians than the averages, but the difference is not very striking.

The median values per country of *the lowest absolute RMSE's per variable* from Annex 8 have been summarized in Table 8.

Table 8 Overview of the median value per country of the lowest absolute RMSE's per variable

	Rad [kJ]	SSD [hr]	TMin [°C]	Tmax [°C]	Vap [kPa]	Win [m/s]
United Kingdom	**1961**	**1.68**	**1.25**	**1.09**	**0.08**	**0.78**
Ireland	**1634**	**1.44**	**0.99**	**0.88**	**0.04**	**0.87**
Denmark	**1715**	**1.52**	**1.60**	**1.22**	**0.09**	**0.85**
The Netherlands	**1421**	**1.26**	**1.11**	**0.85**	**0.06**	**0.77**
Belgium	**1834**	**1.69**	**1.19**	**1.44**	**0.08**	**0.93**
Switzerland	**1611**	**1.51**	**1.43**	**1.31**	**0.08**	**0.59**
France	**1695**	**1.53**	**1.25**	**1.15**	**0.08**	**0.92**
Spain	**1801**	**1.71**	**1.51**	**1.44**	**0.12**	**1.46**
Portugal	**1715**	**1.61**	**1.25**	**1.28**	**0.10**	**0.88**
Germany	**1406**	**1.29**	**1.02**	**0.92**	**0.05**	**0.64**
Austria	**2088**	**2.00**	**1.69**	**1.83**	**0.11**	**1.28**
Slovenia	**1686**	**1.58**	**1.30**	**1.57**	**0.10**	**1.13**
Italy	**2072**	**2.00**	**1.60**	**1.75**	**0.14**	**1.19**

The highest RMSE's for radiation, sunshine duration, minimum temperature, maximium temperature, vapour pressure or windspeed can be found for respectively Austria (2088. kJ), Austria and Italy (2.00 hrs), Austria (1.69 °C), Austria (1.83 °C), Italy (0.14 kPa), and Spain (1.46 m/s). The lowest RMSE's for radiation, sunshine duration, minimum temperature, maximium temperature, vapour pressure or windspeed can be found for respectively Germany (1406. kJ), the Netherlands (1.26 hrs), Ireland (0.99 °C), the Netherlands (0.85 °C), Ireland (0.04 kPa), and Switzerland (0.59 m/s). In general Ireland, the Netherlands and Germany show the lowest values. Apparently these countries can be predicted the best by simple linear interpolation techniques.

Annex 9 shows figures per country with *the influence of the number of stations and selection criteria* on the interpolation. From Annex 9 the following can be deduced:

- In all countries the performance of the algorithm improves most if the number of stations to be used in the interpolations is increased. Increasing the number of stations from 1 to 2 shows the largest improvement. Switzerland forms an exception: the performance of substitution with the nearest station is better than the use of the 2 nearest stations. This is not the case if the similarity is defined as a combination of proximity and altitude: apparently some Swiss station are located closely to other stations, but are quite different in altitude.
- The results with 4 stations are usually slightly better than with 3 stations. Exceptions are United Kingdom and Denmark. The reason is that the distribution of stations around a reference stations is sometimes irregular, so that the forced selection of a fourth station leads to the inclusion of a faraway station, or of an imbalanced configuration. This situation corresponds with high suitability scores (in Annex 3)
- In Denmark, the Netherlands, Belgium, Italy, and Spain the performance of a fixed number of 4 stations is equally good or better than a variable number of stations as a function of configuration (1-4 stations no ns factor). But if the criterion of configuration is extended with a penalty for sets with two stations and an even stronger penalty for sets with one station (1-4 stations + ns factor), a better

performance is found in almost all countries. Only in the Netherlands the use of a fixed number of 4 stations remains clearly better than the use of a variable number of stations.

- Defining the selection criteria as combination of proximity and distance to the coast causes a better performance than proximity alone in Portugal and Spain only. The reasons that in the other countries the improvement is not visible may be that the algorithm selects the same stations in both cases. This is by definition the case for inland stations. In countries with a large number of inland stations the coastal effect on the overall performance is low (Germany, France, Switserland). Within the coastal zone the algorithm may select stations further away along the coast, so that gain in coastal character is traded off by greater distance. Other reasons may be that the algorithm does not make a distinction between eastern and western coast.
- The combination of proximity and altitude in the selection criteria has a very clear positive effect in Switzerland, Austria, Germany, Portugal and Italy, and a slightly positive effect in France and Spain. The effect is greatest where differences in altitude between nearby stations varies considerably.
- Defining the selection criteria as a combination of proximity, and both altitude and distance to the coast leads to some further improvement in comparison with above mentioned combinations in Austria, Italy, Ireland, France and Spain. In the United Kingdom, Ireland, Denmark, the Netherlands, Belgium, France, Portugal and Spain there is hardly any difference in effect between the alternative selection criteria. In combination with the altitude criterion, the coast criterion has a clear positive effect in Ireland and Italy.

Summarizing it can be concluded:

o Concerning the influence of the number of stations it is clear that a variable number of 1 to 4 stations with a preference for 3 or 4 stations gives the best interpolation results in all countries but the Netherlands.

o With respect to station selection criteria the general pattern is that in the northern countries of the EC, Ireland, United Kingdom, The Netherlands, Belgium and Denmark the use of refined selection criteria leads to only slight improvements, if any at all, in the interpolation results. The largest improvements are found for Italy, Austria, Switzerland, Germany and Portugal, and slight improvements for France and Spain.

Table 9 shows **the regional mean relative performance** of the proposed algorithm per country.

Table 9 Mean relative performance of the algorithm to interpolate the weather of reference stations per country

Region	**Number of reference stations**	**rel. RMSE [rmse rmse^{-1}]**
EC-countries used for development		
United Kingdom	**23**	**1.06**
Ireland	**13**	**1.10**
Denmark	**6**	**1.10**
The Netherlands	**6**	**1.19**
Belgium	**4**	**1.14**
France	**61**	**1.08**
Spain	**58**	**1.20**
Portugal	**11**	**1.18**
Germany	**51**	**1.10**
Bordering countries		
Switzerland	**4**	**1.10**
Austria	**8**	**1.25**
Slovenia	**6**	**1.32**
EC-country used for validation		
Italy	**24**	**1.17**

From Table 9 differences between countries in the mean performance of the proposed algorithm can be deduced:

1 The Northern European countries United Kingdom, Ireland, Denmark, Belgium, France, Germany and Switzerland; These countries show the best results (relative RMSE's from 1.06 [rmse rmse^{-1}] in the United Kingdom till 1.14 [rmse rmse^{-1}] in Belgium).

2 The Mediterranean countries Portugal, Spain and Italy; This group shows worse relative RMSE's (1.18 [rmse rmse^{-1}] in Portugal and 1.20 [rmse rmse^{-1}] in Spain).

The difference between these two groups can be explained by the difference in their climatological system. Northern Europe is mainly under the influence of extensive pressure systems (low- and high pressure cells with an extent of 500-2500 kilometre) while in Southern Europe local convective systems (on a scale of 5-10 km) are more important (Beek, 1991-2). The latter system is much more variable in time and place and therefore less easier to estimate as a function of fixed geographical qualities.

There is no significant difference between the mean performance of the independent set of stations in Italy that was used for the validation of the algorithm and the other mediterrenean countries Portugal and Spain that were used for the development of the algorithm.

Remarkably, The Netherlands show a much worse performance (1.19 [rmse rmse^{-1}]) than the other Northern European countries.

From Annexes 6 and 8 it can be seen that from the countries especially The Netherlands have very low absolute RMSE's in their best possible sets. This leads to higher mean relative RMSE's, because the gap between the lowest prediction errors and the RMSE's of the selected set is wider than for other countries having a larger absolute RMSE's in the best possible sets. One could say that some stations in The Netherlands are in fact 'too good' to be predicted properly by the algorithm.

4 Conclusions and discussion

4.1 The proposed algorithm

An algorithm is proposed to predict daily weather data for any areal unit from the available weather data of meteorological stations. The algorithm can be applied universally, regardless of the density of the stations network.

The study aimed at a procedure to generate daily weather data for seven meteorological variables for 1389 grid cells over the EC throughout a long series of years on the basis of a network of (200-600) meteo stations that is strongly varying in density and over the years. The algorithm incorporates an efficient calculation procedure to meet the goal of this study.

The algorithm shows the following advantages:
- Despite the strongly varying density of the stations network over regions and throughout the years, weather analysis on grid cells becomes possible for a series of years.
- The proposed algorithm is developed and validated with the help of *reference stations*, but will be applied to estimate the meteorological variables on *gridpoints*. However, the geometrics of the network of reference stations differs from the geometrics of the (50 km x 50 km) network of gridpoints. The average distance from a reference station to another station is larger than the distance from a gridpoint to a station. The distances between stations are more regular than the distances between gridpoints and stations; a gridpoint can be located very close to a station, stations are almost never located very close to each other. It is clear that a gridpoint located closely to a station is best estimated by using the data of this station. The proposed algorithm offers this possibility: the number of used stations is variable, and will indeed select only this station.
- There is good reason to assume that the weather data values of one station represent a more realistic day to day weather pattern than the averaged values of several stations. Therefore the proposed algorithm is expected to deal properly with gridpoints. For the same reasons the algorithm with variable number of stations is preferred above the alternative algorithm using a fixed number of 4 stations, while weighting inversely for distance, even though the latter gives equally good results when applied to reference stations. Comparing a variable number of stations with a fixed number of stations, not much difference is expected in regions like the centre of France with a regularly distributed network of stations. However, a variable number of stations is performing better in exterior regions where no 4 surrounding stations can be found like e.g. Northern Scotland, Northern Denmark, Southern Italy, and most islands. In those regions the algorithm chooses only a relatively nearby located single station, or two of them. If the distribution of stations around a reference station is irregular, the forced selection of a fourth station leads to the inclusion of a faraway station, and an imbalanced configuration.
- During the development of the algorithm, attention has been focussed on individual stations. In several cases the advantage of a variable as opposed to a fixed number of stations turned out to be quite high. This advantage will even be more apparent

while estimating the weather on grid cells.
- The accuracy of the weather analysis on grid cells can be improved by increasing the number of meteo stations without changing the procedure to select the stations to be used.

4.2 Development and validation of the algorithm

4.2.1 Selected sets of stations per reference station

From the selected sets of stations per reference station the following can be concluded:
- The *absolute performance of the linear interpolation alternatives being expressed as the absolute values of the RMSE's per weather variable* is less accurate in Southern Europe and in mountainous regions.
- The *best possible configuration between stations* shows a clear *network of coastal stations* selecting each other, as well as a *network of high-altitude stations*. The last network is most striking in the Spanish highland. *Climatic barriers* are formed by the Pyrenees and the Alps.
- Because the algorithm doesn't take into account all local effects, the *configuration of the algorithm* shows a more regular pattern. But in general the patterns of the network representing the best possible configuration and of the network created by the algorithm are quite similar.
- If *the use of only one station* yields the best estimate, this concerns mostly stations at very short distance from each other.
- The *number of stations per set* is in general higher in the best performing sets than in the sets selected by the proposed algorithm.
- In most cases the algorithm gives a good to reasonable relative performance; in 10% of the cases the performance with the use of other sets would lead to a considerably better performance. The reference stations for which the station selection with the algorithm was less successful are mostly concentrated in a few regions in Southern Germany, Austria and Slovenia, in France around the Central Massif, in the interior of Spain, and in (coastal areas in) Italy.

4.2.2 Regional results

From the *regional results* the following can be concluded:
- *Comparing alternative selection procedures*, shows that the best performance of the algorithm is reached when the *number of stations* to be used in the interpolations is 3 or 4. Regardless of the involved similarity criteria, increasing the number of stations from 1 to 2 shows the largest improvement. It can be concluded that the use of more than 4 stations does not lead to further improvement. If the number of stations is variable as a function of configuration, the performance is less than reached with a fixed number of 4 stations. But if the criterion of the algorithm with a variable number of stations is extended with a penalty for sets

with two stations and an even stronger penalty for sets with only one station, a better performance is found.

Defining *similarity* as a combination of proximity, altitude and distance to the coast always leads to some improvement in comparison with criteria based on proximity or on combinations of proximity and coast, or proximity and altitude (1-3%). Extending the proximity criterion with the altitude-criterion always improves the performance.

- In general it appears that the selection algorithm for interpolation should take into account the use of a variable number of (1-4) stations, selection of stations as a function of proximity, altitude and distance to the coast, and a surrounding configuration of stations with a preference for the use of more than 2 stations. This confirms the proposed algorithm formulated in (3).
- Inversely *weighting for distance* shows the same performance as unweighted interpolation according to the proposed algorithm.

  It appears that the influence of the distance is already accounted for optimally within the station selection procedure of the proposed algorithm without weighting.
- *Variable specific differences* can be deduced. It appears that regardless of the number of stations to be used, the meteorological variables can be divided into three groups:

  1 radiation and sunshine duration show the best performance;

  2 minimum temperature, maximum temperature and vapour pressure take a medium position;

  3 windspeed shows clearly a worse performance than the other variables.

  The use of the proposed average relative RMSE appears to be an appropriate criterion to compare the interpolation algorithms.
- Comparing *differences between countries*, the lowest *absolute RMSE's per variable* are summarized per country: Belgium behaves climatologically most uniform. More climatological difference within a country is most obvious for Spain.

  In general Ireland, the Netherlands and Germany can be predicted the best by simple linear interpolation techniques.
- Comparing *differences between countries* in *the mean relative performance* of the proposed algorithm the following can be deduced:
- Considering *the influence of the number of stations and selection criteria*:
  - In all countries the mean relative performance of the algorithm improves most if the number of stations to be used in the interpolations increases from 1 to 4.
  - Only in the Netherlands the use of a fixed number of 4 stations remains clearly better than the use of a variable number of stations.
  - Defining the selection criteria as a combination of proximity, altitude and distance to the coast leads to some improvement in comparison with using a smaller set of criteria, in Germany, Austria and Italy. In the United Kingdom, Ireland, Denmark, the Netherlands, Belgium, France, Portugal and Spain there is hardly any difference between alternative selection criteria.
  - Defining the selection criteria as a combination of proximity and distance to the coast causes a better performance than proximity alone in Portugal and Spain only. The reason that in the other countries the improvement is not visible may be that the algorithm selects the same stations in both cases. This is by definition the case for inland stations. In countries with a large number of inland stations the coastal effect on the overall performance is low (Germany, France,

Switzerland). Within the coastal zone the algorithm may select stations further away along the coast, so that gain in coastal character is traded off by greater distance. Other reasons may be that the algorithm does not make a distinction between eastern and western coasts.
  - The combination of proximity and altitude in the selection criteria has a very clear positive effect in Switzerland, Austria, Germany, Portugal, and Italy, and a slight positive effect in France and Spain. The effect is greater where difference in altitude between nearby stations varies considerably.
- Considering *differences between regions for the proposed algorithm*:
  - *Two groups of countries* can be recognized:
    The Northern European countries United Kingdom, Ireland, Denmark, Belgium, France, Germany and Switzerland show the best results.
    The Mediterranean countries Portugal, Spain and Italy show worse relative RMSE's.
    The difference between these two groups can be explained by the difference in their climatological system. Northern Europe is mainly under the influence of extensive pressure systems (low- and high pressure cells with an extent of 500-2500 kilometre) while in Southern Europe local convective systems (on a scale of 5-10 km) are more important (Beek, 1991-2). The latter system is much more variable in time and space and therefore less easier to estimate as a function of fixed geographical qualities.
  - There is no significant difference between the mean relative performance of the independent set of stations in Italy that was used for *the validation of the algorithm* and the other mediterranean countries Portugal and Spain that were used for the development of the algorithm.
  - *The Netherlands show a much worse performance* than the other Northern European countries.
    It can be seen that from the countries especially The Netherlands have very low absolute RMSE's in their best possible sets. This leads to higher mean relative RMSE's, because the gap between the lowest prediction errors and the RMSE's of the selected set is wider than for other countries having larger absolute RMSE's in the best possible sets. One could say that some stations in The Netherlands are in fact 'too good' to be predicted properly by the algorithm.

4.2.3 Influence of missing data

In this study results are partly obscured by the occurence of missing data in the investigated period of 5 years. It would be interesting to compare the results of this study with a future study that can use data belonging to a more recent period without that many missing data. It would also be interesting to investigate if the results might benefit from a longer period of study.

4.3 Possibilities for improvement of the algorithm

It is obvious that the performance of the algorithm depends strongly on the meteorological processes underlying the investigated variables. Consequently the algorithm can be improved by implementing more meteorological knowledge into it:

- The algorithm could be made more variable-specific. One could try to group the meteorological variables into classes related to the spatial gradient of the processes underlying the variables, and applying different weighting factors for every class: E.g. the use of more surrounding stations for variables with a low spatial gradient.
- The algorithm could be made region-specific, according to differences in the processes underlying the variables. All kinds of expected region-specific processes that influence the performance of the algorithm can be investigated by the selection of related testing regions.

Before a complex expansion of the algorithm takes place, it might be useful to consider its effect on the final goal: the simulation of agricultural production possibilities.

The difference between the performance of the proposed algorithm and the best results of any of the methods of (Beek, 1991-1) might be that small, that it might be more effective to concentrate first on other than meteorological input data. If in future simulations the meteorological data are not found to be accurate enough, one might consider further optimization of the algorithm aimed at specific shortcomings.

On the other hand, the best way to improve the geographic coverage of weather data is to increase the station density. It is known that the availability of weather data will improve in the future by an increase in number of stations from the 275 used in this study to about 650. If for each grid cell a representative station could be found, the interpolation procedure is trimmed back to the selection of that station and assignment of its weather data to the grid cell.

The estimation of daily rainfall could be improved with the use of an extra number of separate rainfall stations on top of the overall meteorological stations.

4.4 Other techniques

The algorithm only makes use of the actual stations data itself, without additional information on common weather type characteristics like direction of wind, air pressure, or the continental or maritime nature of the air mass. Taking into account this information would require other interpolation techniques.

To estimate weather on the basis of grid cells in the *current year*, one could consider the use of meteorological remote sensing images. However, construction of *historical series* over longer periods will remain impossible.

Relative performance is relative compared to the best possible linear interpolation alternative. It would be interesting to compare the results with the best possible results of other methods, esp. Kriging using the geographical qualities altitude and distance to the coast as co-factors. Such a Kriging method would be able to take into account temporal and cross correlations between the variables and therefore is expected to give better estimates. However, even if the co-Kriging method appears to give much better results, it will be a (too) heavy computer-technical effort to calculate the weighting factors for all variables for every day for every location.

References

Beek, E.G., 1991-1. *Spatial interpolation of daily meteorological data. Theoretical evaluation of available techniques.* Report 53.1. Wageningen, The Netherlands. DLO Winand Staring Centre.

Beek, E.G., 1991-2. *Spatial interpolation of daily meteorological data. Using kriging to predict daily rainfall in North-Western Europe.* Report 53.2. Wageningen, The Netherlands. DLO Winand Staring Centre.

Beek, E.G., A. Stein and L.L.F. Janssen, 1992. *Spatial variability and interpolation of daily precipitation amount.* Stochastic Hydrology and Hydraulics 6: 304-320.

Brink, J.W. van den, A.K. Bregt, C.A. van Diepen, J.H. Oude Voshaar, 1991. *Interpolation study of meteorological data.* Wageningen, The Netherlands. DLO Winand Staring Centre, DHV Consultants. Internal Report.

Bulens, J.D., 1991. *Crop Growth Monitoring System. user manual. part 1: weather.* DLO Winand Staring Centre, Wageningen, The Netherlands. Joint Research Centre, Ispra, Italy.

Diepen, C.A. van, J. Wolf, H. van Keulen and C. Rappoldt, 1989. *WOFOST, a simulation model of crop production.* Soil Use and Management 5: 16-24.

Drift, J.W.M. van der, and C.A. van Diepen, 1992. *The DBMETEO data base on the countries of the European Communities. Description of the data and data-treatments. Technical Document 4.* DLO Winand Staring Centre, Wageningen, The Netherlands. Joint Research Centre, Ispra, Italy.

Hijmans, R.J., I.M. Guiking-Lens and C.A. van Diepen, 1994. *WOFOST. User guide for the WOFOST 6.0 crop growth simulation model.* Technical Document 12. Wageningen, The Netherlands. DLO Winand Staring Centre.

Reinds, G.J., 1991. *DBMETEO: a programme to store, retrieve and analyze meteorological data sets.* Wageningen, The Netherlands. DLO Winand Staring Centre. Joint Research Centre, Ispra, Italy.

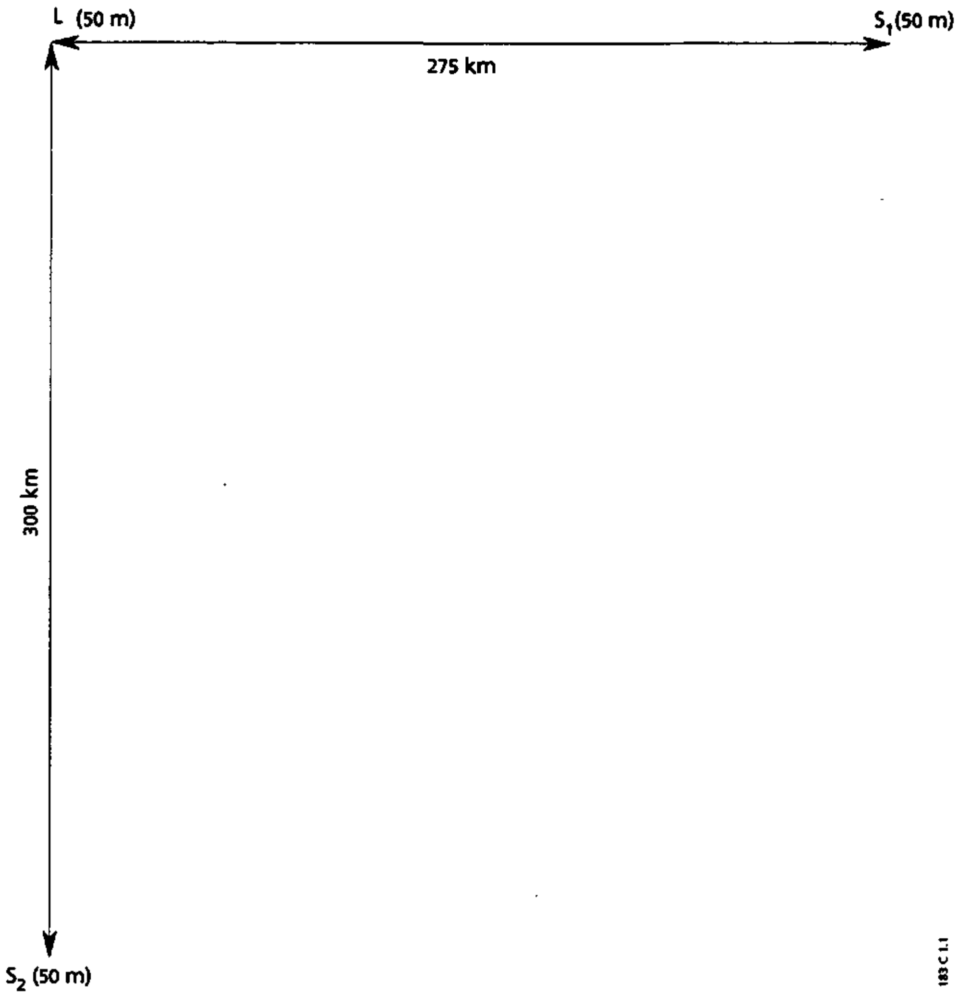
Supit, I., Hooyer, A.A., C.A. van Diepen (eds), 1994. *System description of the WOFOST 6.0 crop simulation model implemented in CGMS.* Agriculture series EUR 15956. European Commission. Joint Research Centre, Ispra, Italy.

Annexes

Annex 1 Visualizing the effect of the different components determining the station selection

The effect of including the distance from any location L to the centre of gravity of a set of stations as criterion for the identification of an optimum set of stations for location L.

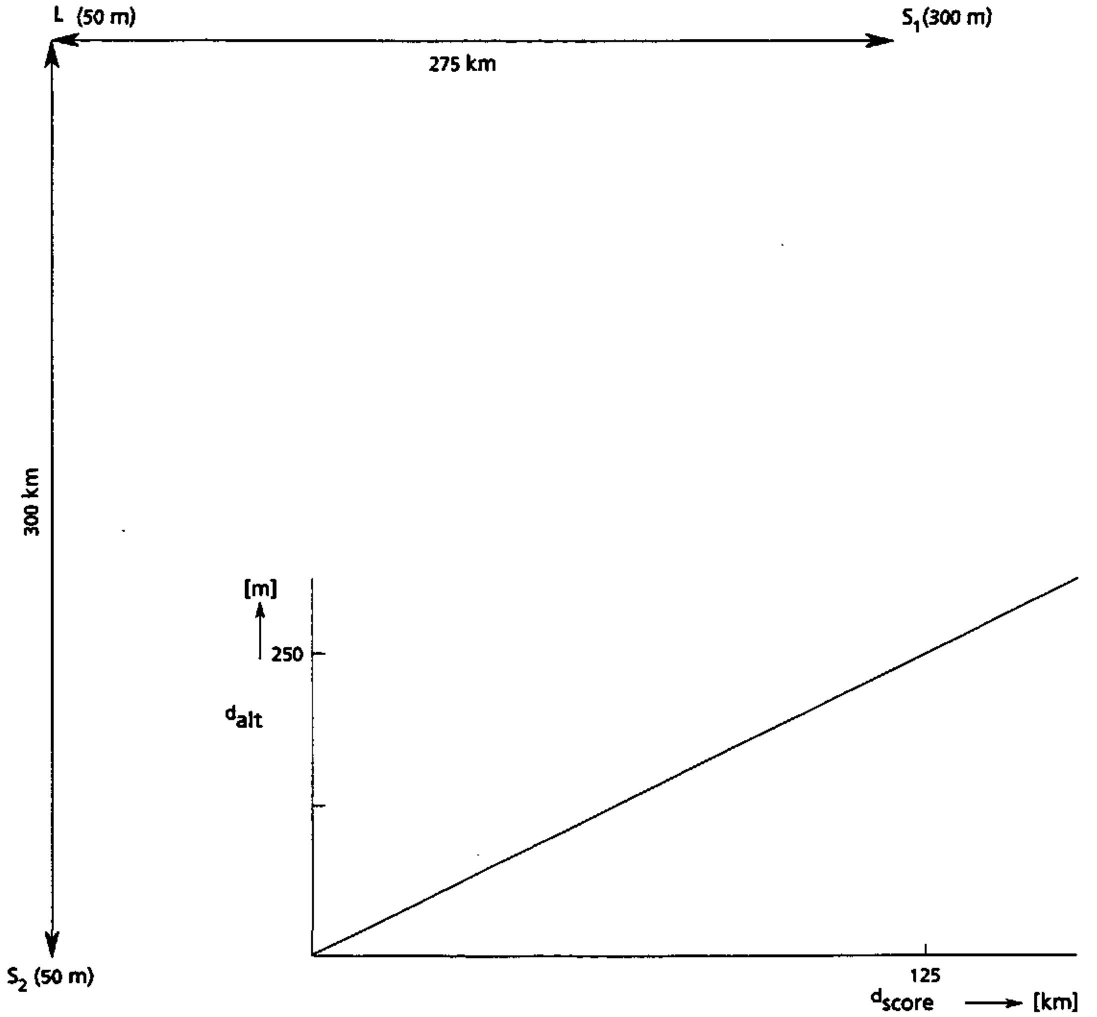
Annex 1.1 Distance



Distance

Scores: station S_1: 275 km
station S_2: 300 km
S_1 most similar

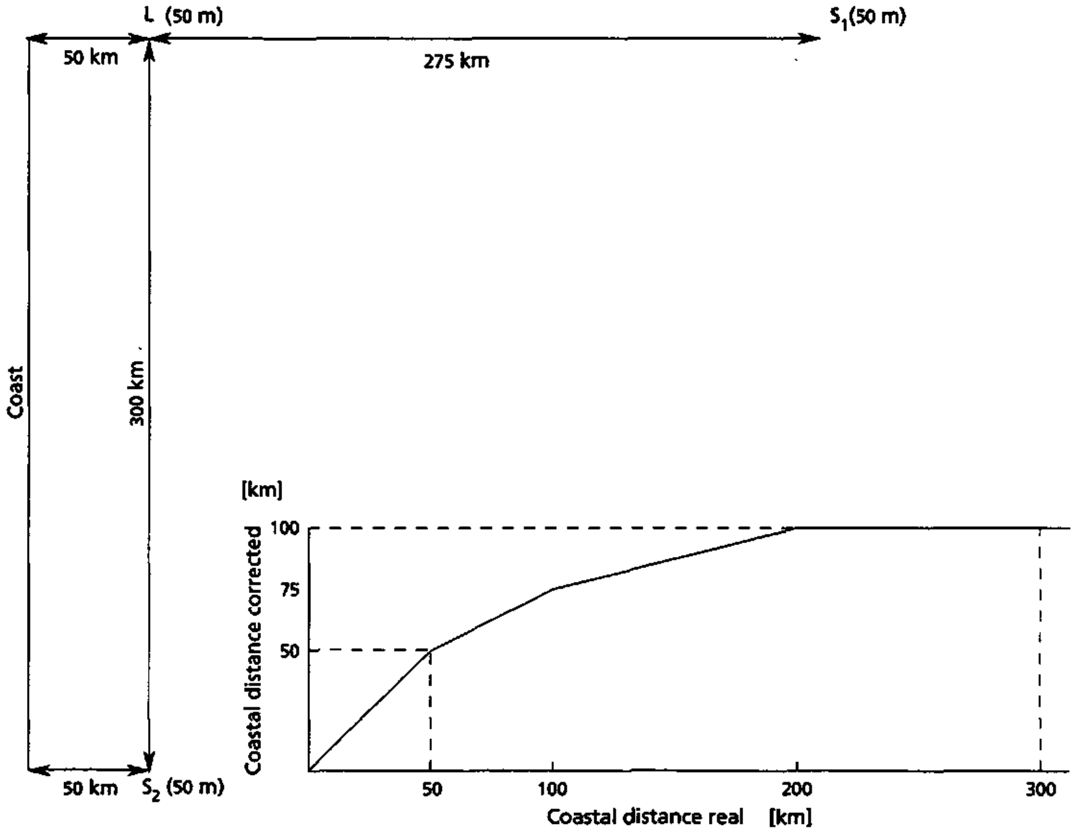
Annex 1.2 Distance and altitude



Distance + altitude

Scores: station S_1: 275 + 0.5* (300-50) = 400 km
station S_2: 300 + 0.5* (50-50) = 300 km
} S_2 most similar

Annex 1.3 Distance and coast

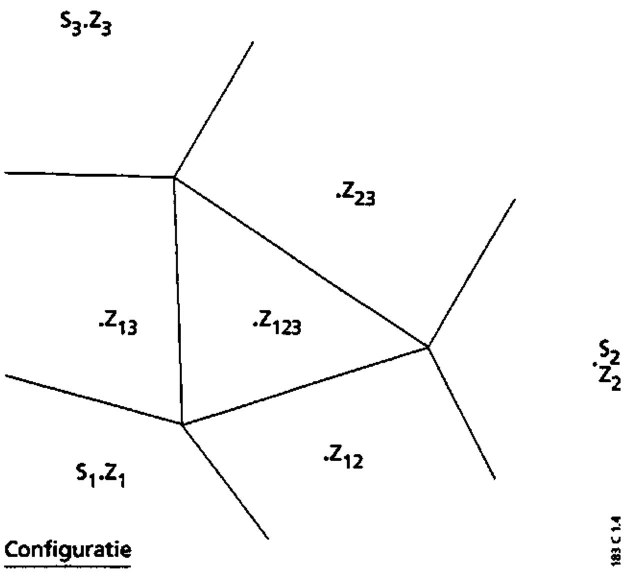


<u>Distance + coast</u>

Scores: station S_1: 275 + (100-50) = 325 km
station S_2: 300 + (50-50) = 300 km
} S_2 most similar

183 C 1.3

Annex 1.4 Configuration



Configuratie

Annex 2 Validation program VALMET

The Fortran program VALMET (VALidation on METeo stations) performs the following steps in the validation procedure:

1. Definition of the selection criteria for stations to be used in terms of kind and number of stations. The program offers several alternatives to estimate weather variables with the use of a fixed number of 1, 2, 3, or 4 stations, or a variable number of 1-4 stations, selecting the stations by (combination of) the criteria proximity, and similarity in distance to the coast, and in altitude. It is also possible to incorporate a preference for sets of stations with more than one or two stations.
2. Definition of the test-region. The program asks for the (regional) set of reference stations to estimate the weather variables.
3. Selection of sets of similar stations. For every reference station it selects the most similar stations to be used for the estimation of rainfall, as well as the 98 most promising sets of stations to be used for the estimation of the other meteorological variables.
4. Estimation of weather variables. For every reference station it calculates for the most promising 98 sets the interpolated values for all meteorological variables.
5. Calculation of reference station statistics. For every reference station it calculates for the most promising 98 sets the statistics referred to in 2.4, indicating the 'goodness of fit' of the predicted values in comparison with measured data.
6. Calculation of regional statistics. For every specified set of reference stations it calculates regional means of the relative rmse and ranking of the 98 most promising sets.
7. Output generation. The results of the first six steps are presented in tables and (as an option) in maps.
8. The REGVAL (REGionalize VALidation) program. The REGVAL program is a postprocessing program of the VALMET program. It offers the possibility to derive regional statistics for a subset of the reference stations processed by the VALMET program.

These steps will be discussed into more detail now in separate sections.

The presented VALMET program does not allow any weighting for distance as described in Section 3.2.2.

A second version of the VALMET is used to achieve the results for the interpolation while weighting for distance.

The program expects the user to answer interactively four questions. The offered options can be returned by the user case-insensitive. If the user enters an invalid option the program repeats the question.

2.1 Definition of the interpolation algorithm

Once the program is started, the main routine asks for the number of stations to be used to estimate weather variables:

What is the number of stations to be used in the interpolations:
variable 1- 4 most similar: 0
fixed 1 most similar: 1
fixed 2 most similar: 2
fixed 3 most similar: 3
fixed 4 most similar: 4

enter number: 3

Next the program asks the user to define the similarity criteria to select the stations

How do you wish to define similarity:
Proximity: P
Proximity + Altitude: A
Proximity + Coast: C
Proximity + Altitude + CoastT

enter type of similarity: P

Afterwards the program offers the possibility to incorporate a preference for sets of stations with more than one or two stations:

Do you wish to apply a score-correction in relation to the number of stations of a combination?
yes: Y
no: N

enter y or n :y

At this moment the user is finished with the definition of criteria for similarity of stations to be used to estimate the weather variables.

2.2 Definition of the test-region

On the user's terminal some available test-regions are displayed:

Some available test-regions:

DBMETEO	*DB*
Calibration region	*CA*
Validation region	*VA*
United Kingdom	*UK*
Ireland	*IR*
Denmark	*DM*
The Netherlands	*NL*
Belgium	*BG*
Switzerland	*SW*
France	*FR*
Spain	*SP*
Portugal	*PT*
Germany	*GM*
Austria	*AU*
Italy	*IT*

Enter code of region to be tested ==> nl

The program searches for a region-file with the two characters of the code and the extension '.REG' (e.g. NG.REG). Each record of this ASCII-file contains the station number of one reference station of the region.

This file must be present on the directory for validation of the interpolation program (specified in the file filenames.dat). Some available test-regions are suggested, but one is free to select any other set of reference stations, as long as there exists a region-file, corresponding with the entered code.

If the region-file is found, it is opened. The program displays on the screen:

Opening input file: diskl:[jrc]nl.reg

If the number of stations is fixed the program searches for a file with the best statistics for all reference stations. If this file is not found, it is tried to produce the file by the subroutine BEST, the program displays:

Running BEST to produce diskl:[jrc]dbybest.m0st

BEST needs the score file with the best statistics of all reference stations dbyscore.m0st. If BEST cannot find this file, the program is stopped and displays on the terminal:

Cannot find input file: dbyscore.m0st
First run the VALMET option to produce it.

If dbyscore.m0st is available BEST derives the best statistics for every reference station from it and writes it to dbybest.m0st.
Next the main program opens dbybest.m0st and displays on the screen:

Note that the occurrence of climatic barriers is no longer explicitly part of the suitability score. However since the calculation of the difference-score already disqualified stations on the other side of climatic barriers, no climatic barriers will occur anymore between the reference station and the seven most similar stations.

The sets are sorted on their suitability score. The stations of the set with the lowest score are used for the prediction of daily values for the other meteorological variables of the reference station.

For practical reasons not all different sets of maximum four stations of all stations within DBMETEO are investigated. Theoretically, it is possible that the set with the lowest score also consists of other stations than the seven stations with the lowest difference-score. However, it is unlikely, especially for the configuration of the available stations within DBMETEO.

2.4 Estimation of weather variables

In this section the calculation of the interpolated values for all daily meteorological variables of a reference station takes place.

First all necessary meteo data are read:

- o All records of the DBMETEO file of the reference station are read. For the period 1975-1979 all daily meteorogical values are put into arrays, specifying the year, month and day. The integer values are converted to real values and realistic units (radiation in kJ, sunshine duration in hrs, maximum and minimum temperature in °C, humidity in kPa, windspeed in m/s, rainfall in mm).
- o All records of the DBMETEO-file of the station used for the prediction of rainfall are read. For the period 1975-1979 the daily rainfall data are converted to real values in mm, and put into an array specifying the year, month and day.
- o Then a loop is started of all selected stations to be used for the prediction of the other meteorological variables. For every selected station all records of the DBMETEO-file are read. For the period 1975-1979 the daily data of the other meteorological variables are converted to real values and realistic units (radiation in kJ, sunshine duration in hrs, maximum and minimum temperature in °C, humidity in kPa, windspeed in m/s, rainfall in mm) and put into arrays specifying the year, month and day as well. Values for maximum and minimum temperature, and humidity are corrected as if being present at the altitude of the reference station (described in 2.1.2).

After the last selected station is processed like this, the actual prediction of the daily weather of the reference station takes place:

For all meteorological variables but rainfall the arrays specifying the year, month and day of all selected stations are averaged for every day in the period 1975-1979.

A restriction was made for missing values. If on a certain day within the period 1975-

1979 missing values occur for:

- o any of the meteorological variables in the DBMETEO file of the reference station;
- o rainfall in the DBMETEO file of the station to be used for the prediction of rainfall of the reference station;
- o or for any of the other investigated meteorological variables in the DBMETEO file of any of the selected stations to be used for interpolation, a missing value array is filled indicating the year, month and day of the missing value. For these days no prediction of any of the meteorological variables takes place.

2.5 Calculation of reference station statistics

This section deals with the calculation of the statistics indicating the 'goodness of fit' of the predicted values of a set in comparison with the measured data of every reference station. The reference station statistics (RMSE's) for every meteorological variable are calculated. For every day the squares of the difference between predicted and measured values are calculated. These squares are summarized for the whole period. The number of days for which prediction takes place are counted. After division of the summarized squares by this number, the root is taken, resulting in the RMSE statistics of every variable according to (4).

2.6 Calculation of regional statistics

Next the calculation of regional means of the statistics of all involved reference stations takes place.

Again it makes a difference whether the number of stations is fixed (only one set is processed) or variable (98 sets are processed).

Variable

For every reference station the mentioned 98 sets are sorted according to the RMSE of every variable. For every set and variable a relative RMSE is calculated by division of the absolute RMSE with the lowest RMSE of all 98 sets. The relative RMSE is an indicator for the goodness of the prediction of a set in comparison to the best possible prediction of all sets: A value of 1.00 indicates the optimum prediction, a value of e.g. 1.15 indicates a prediction of 15% less than the optimum one.

In addition to the variable-specific relative RMSE's, an average relative RMSE of every set is calculated as the average of the relative RMSE's of the variables radiation, sunshine duration, minimum temperature, and maximum temperature. These variables are selected because they are expected to be the most important ones as input data for the crop growth model and expected to contribute more variation in yield than the other variables (windspeed and vapour pressure).

An average relative RMSE of e.g. 1.20 indicates that the combined prediction of

Table 2.1 bgyranks.m0st

Reference stations:		
6400		
6447		
6476		
6999		
score rnk	aver. rnk	rmse rel
1	18.50	1.13
2	5.00	1.09
3	28.00	1.16
4	13.75	1.13
5	13.25	1.13
6	48.25	1.31
7	23.00	1.16
8	25.25	1.15
9	35.25	1.19
10	19.25	1.13
......a.s.o......		
95	96.00	1.78
96	94.25	1.66
97	91.50	1.61
98	97.75	1.95

Visualizing the results; the opt- and alg-file

So far all output results into tables. The VALMET-program is developed in a software environment linked to the geographical information system ARC/INFO. This enables to translate the reference station results into maps.
Two types of maps are distinguished:

1. Maps visualizing for all involved reference stations the by the **algorithm** selected set of stations for interpolation. To realize these maps the '**alg**'-files are produced.

   The name of this file is constructed as follows:
   1 two characters of the region code,
   2 one character indicating whether (y or n) a score correction is applied for sets with one or two stations,
   3 three characters forming 'alg',
   4 four characters extension, indicating the number of stations to be used and the similarity definition (e.g. the extension **.m3sp** indicates **most** similar **3** stations in terms of **p**roximity).

   All together this ends up in e.g. an outputfile named nlyalg.m3sp.

   An alg-file contains on every line one couple of wmo-numbers of stations. The first number refers to the reference station, followed by the number of one of the related stations of the set that is used by the algorithm.

2. Maps visualizing for all involved reference stations the interpolation set of stations that is found between the 98 alternative sets with the best statistics. To realize these maps the '**opt**'-files are produced.
   The name of this file is constructed as follows:
   1 two characters of the region code,
   2 one character indicating whether (y or n) a score correction is applied for sets with one or two stations,
   3 three characters forming 'opt',
   4 four characters extension, indicating the number of stations to be used and the similarity definition (e.g. the extension **.m0st** indicates **m**ost similar variable (**0**) number of **s**tations in **t**erms of all similarity criteria together).

All together this ends up in e.g. an outputfile named bgyopt.m0st.

An opt-file contains on every line a couple of wmo-numbers of stations. The first number refers to the reference station, followed by the number of one of the related stations of the set with the best statistics.

In case of a **variable** number of stations an alg- as well as an opt-file are produced. In case of a **fixed** number of stations only the alg-files can be produced.

Table 2.2 and 2.3 give examples of an alg- and an opt-file (respectively bgyalg.m0st and bgyopt.m0st).

Table 2.2 bgyalg.m0st

06400	03797
06400	07015
06447	06999
06447	07015
06447	06370
06476	10501
06476	06999
06476	07090
06999	06447
06999	10501
06999	07061

one is free to select any other set of reference stations, as long as there exists a region-file, corresponding with the entered code.

If the region-file is found, it is opened. The program displays on the screen:

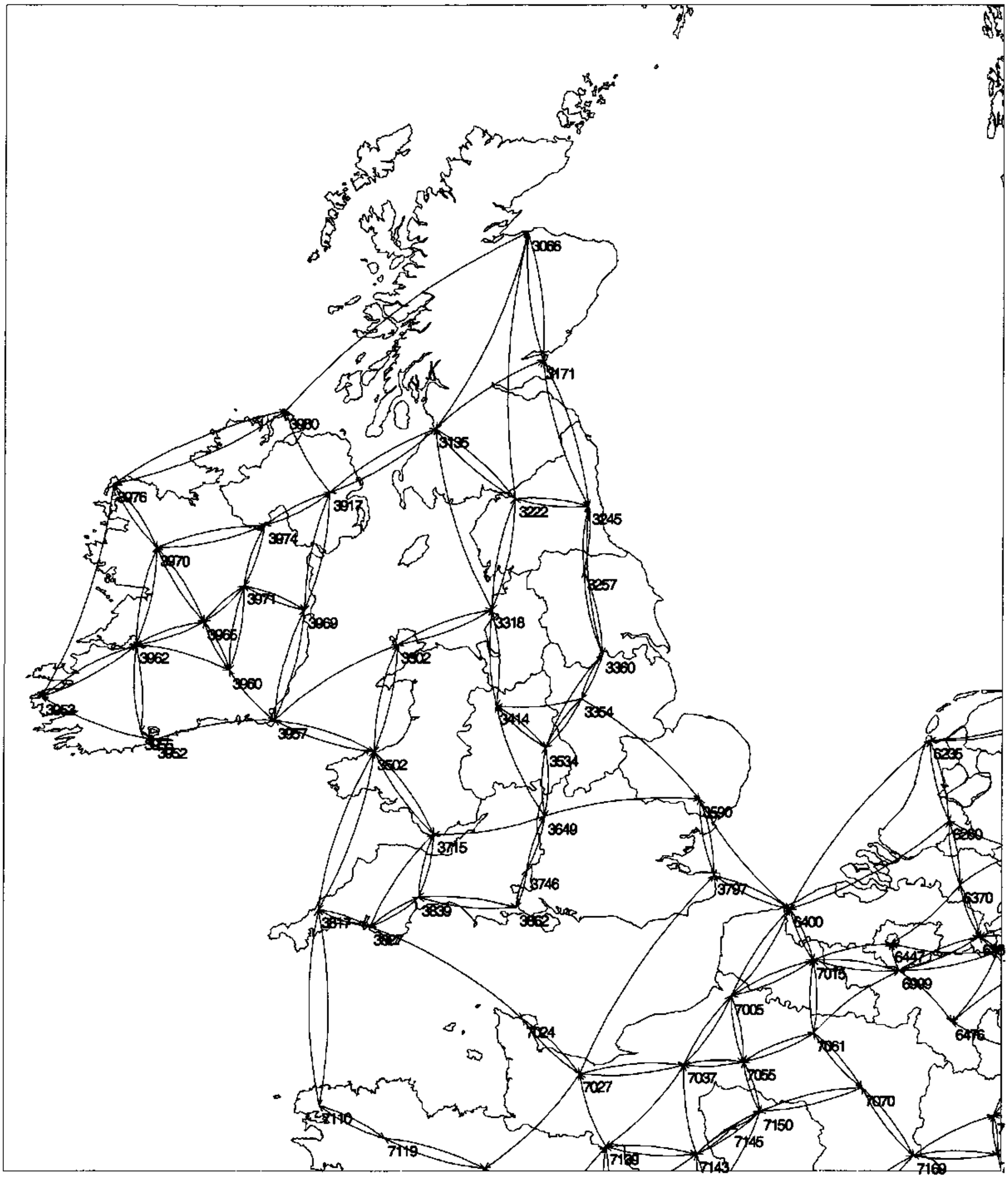
Opening inputfile: disk1:[jrc.vaxaug.action3.validate]nl.reg

The regional results are written to the ranks-file in the same format as the ranks-files directly produced by the VALMET program.

Annex 3 Reference station statistics

This Annex of 282 pages is published as a separate volume with a limited distribution.

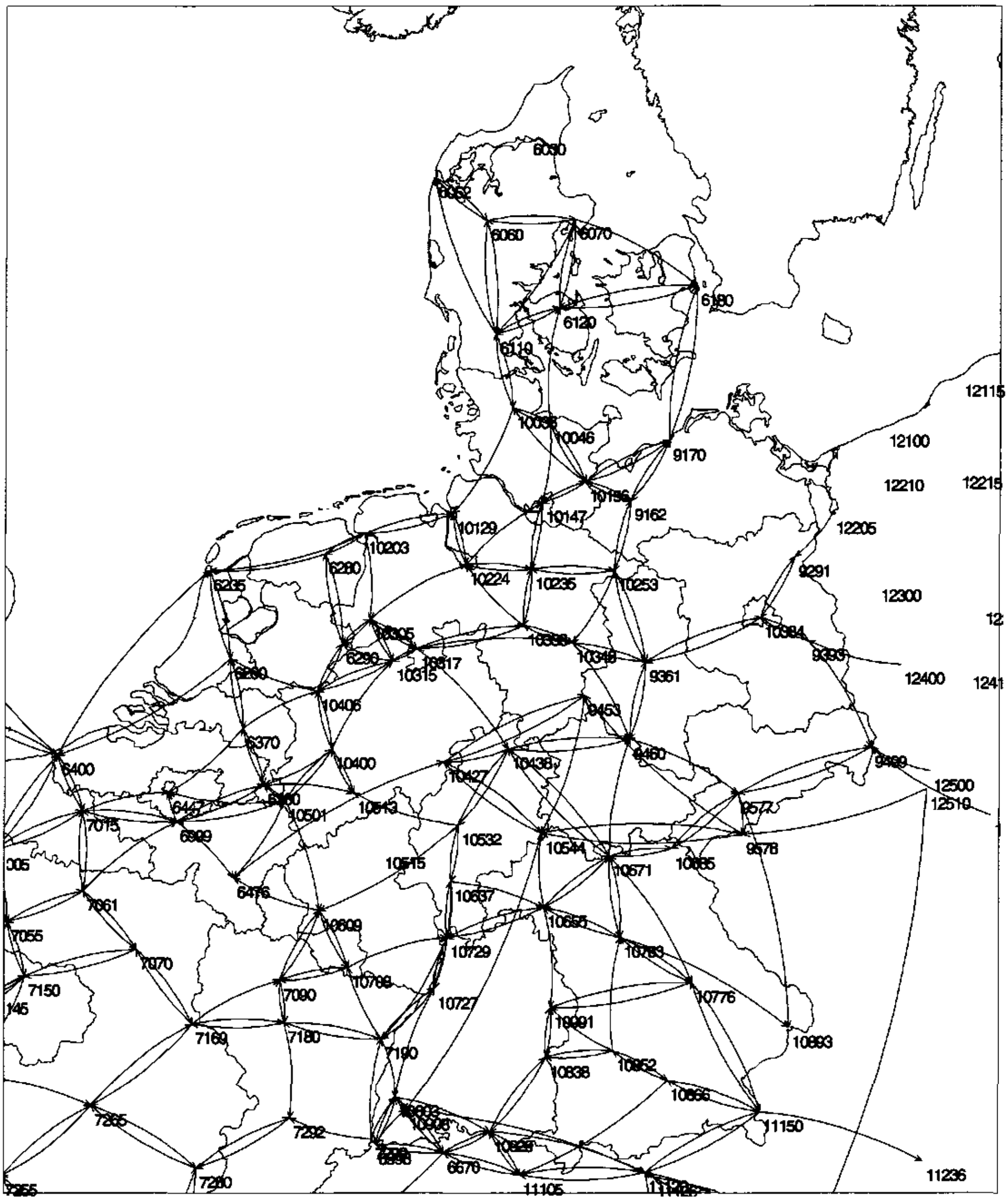
Annex 4 Maps showing for each reference station the best performing set of stations for interpolation of daily meteorological data



Annex 4.1
United Kingdom
Ireland

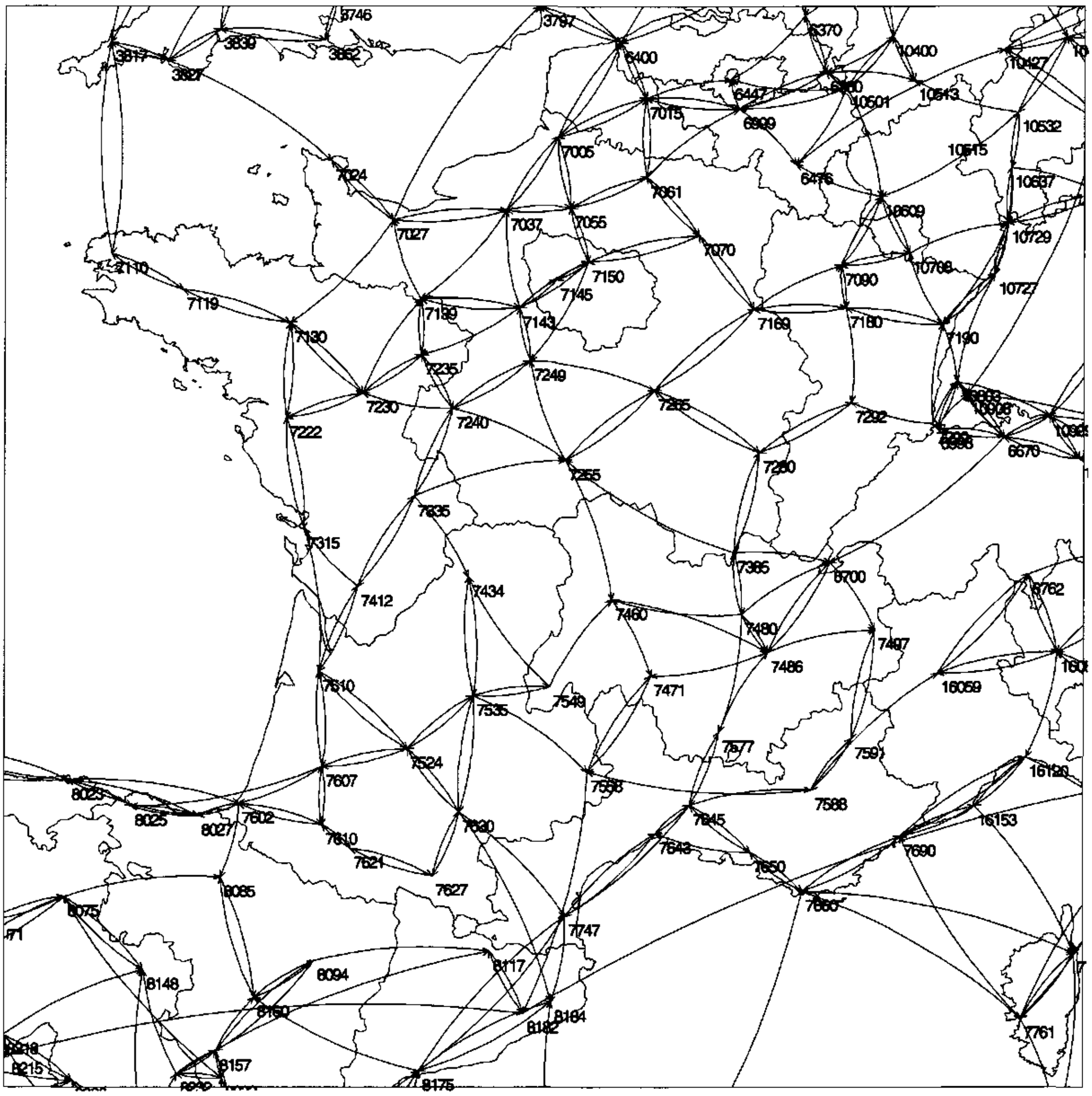
kilometers
0 600

Annex 4.1

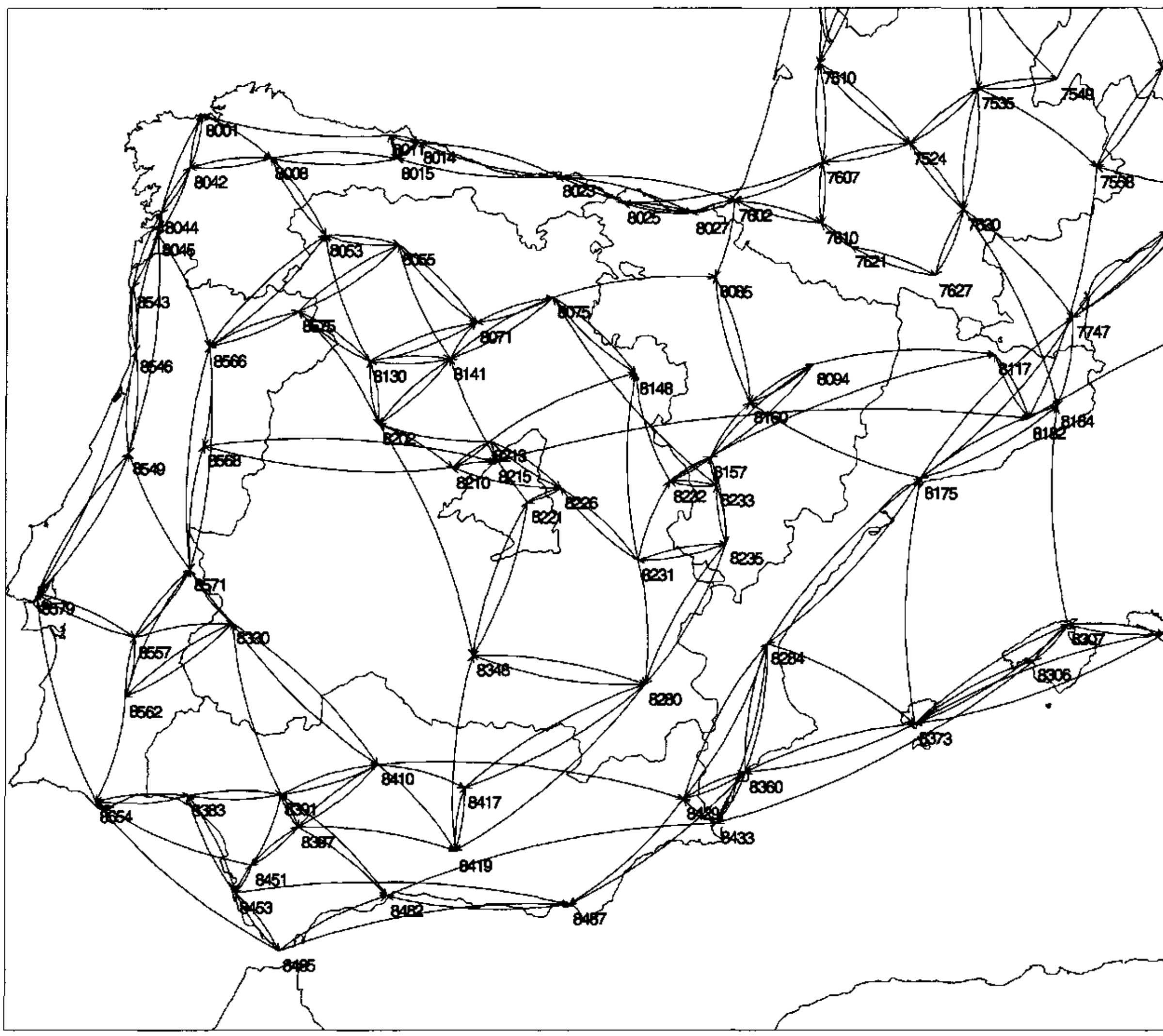


Annex 4.2
Denmark
The Netherlands
Belgium
Germany

kilometers
0 600

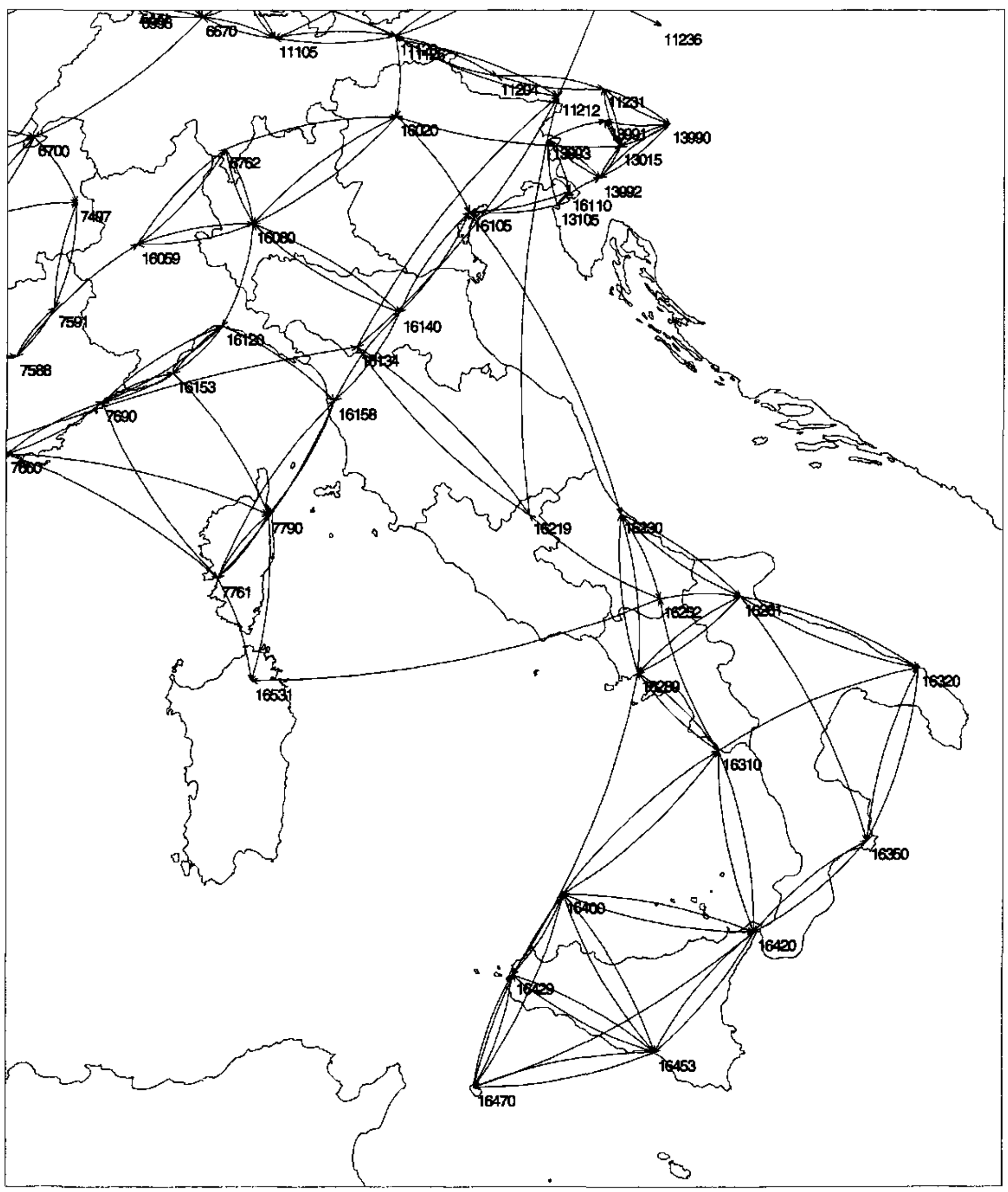


Annex 4.3
France



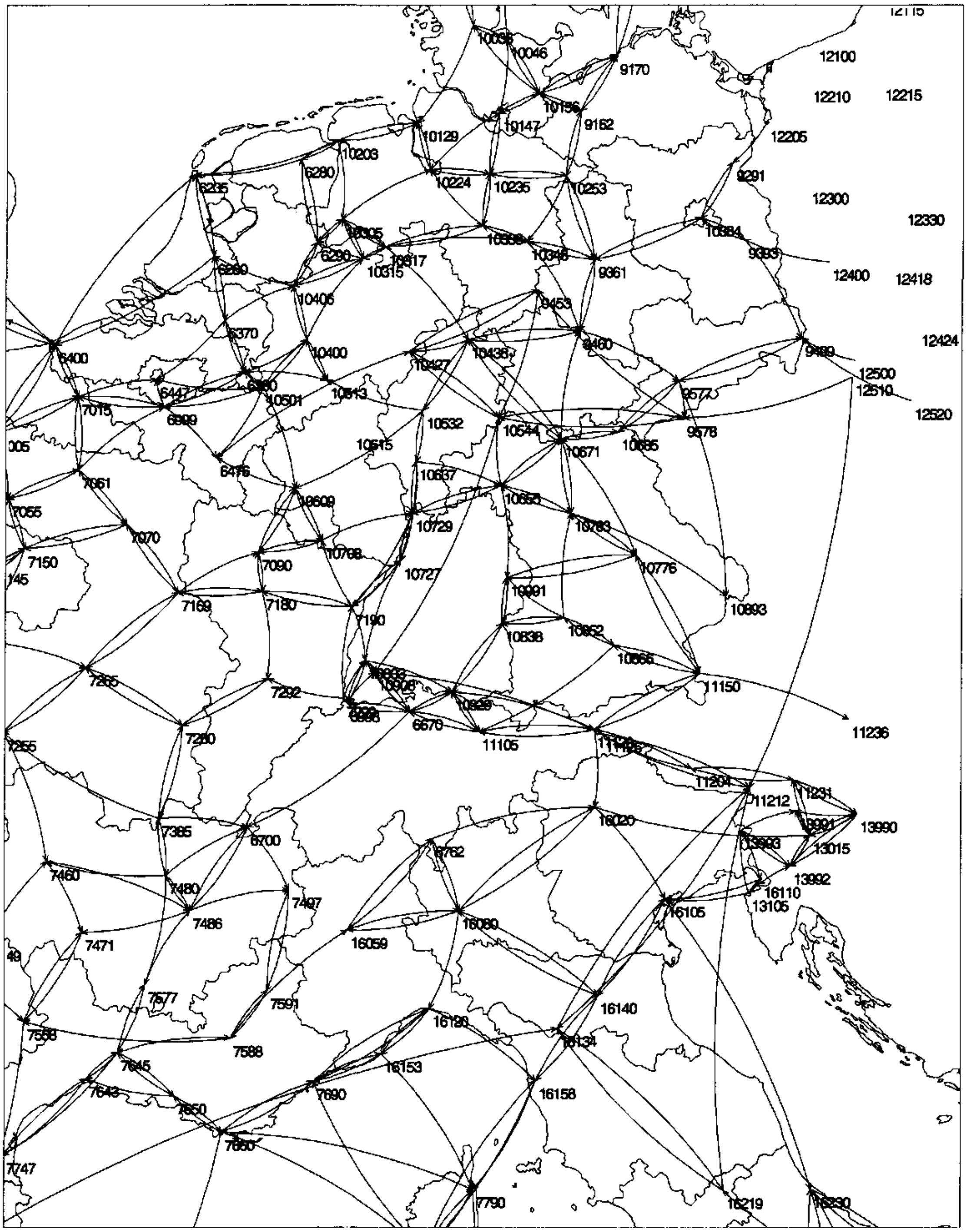
Annex 4.4
Portugal
Spain

kilometers
0 600



Annex 4.5
Italy

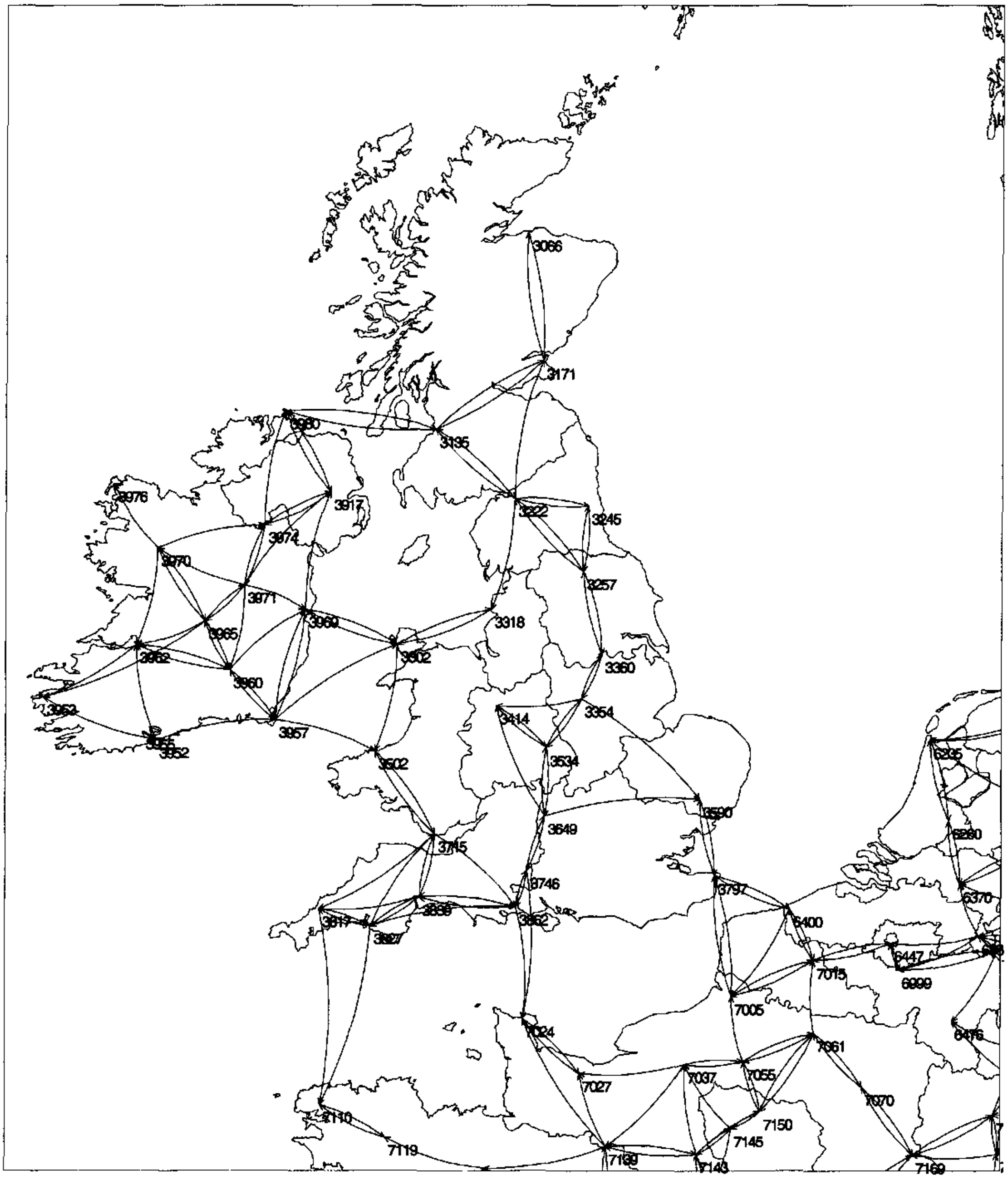
kilometers
0 600



Annex 4.6
Alps and bordering area

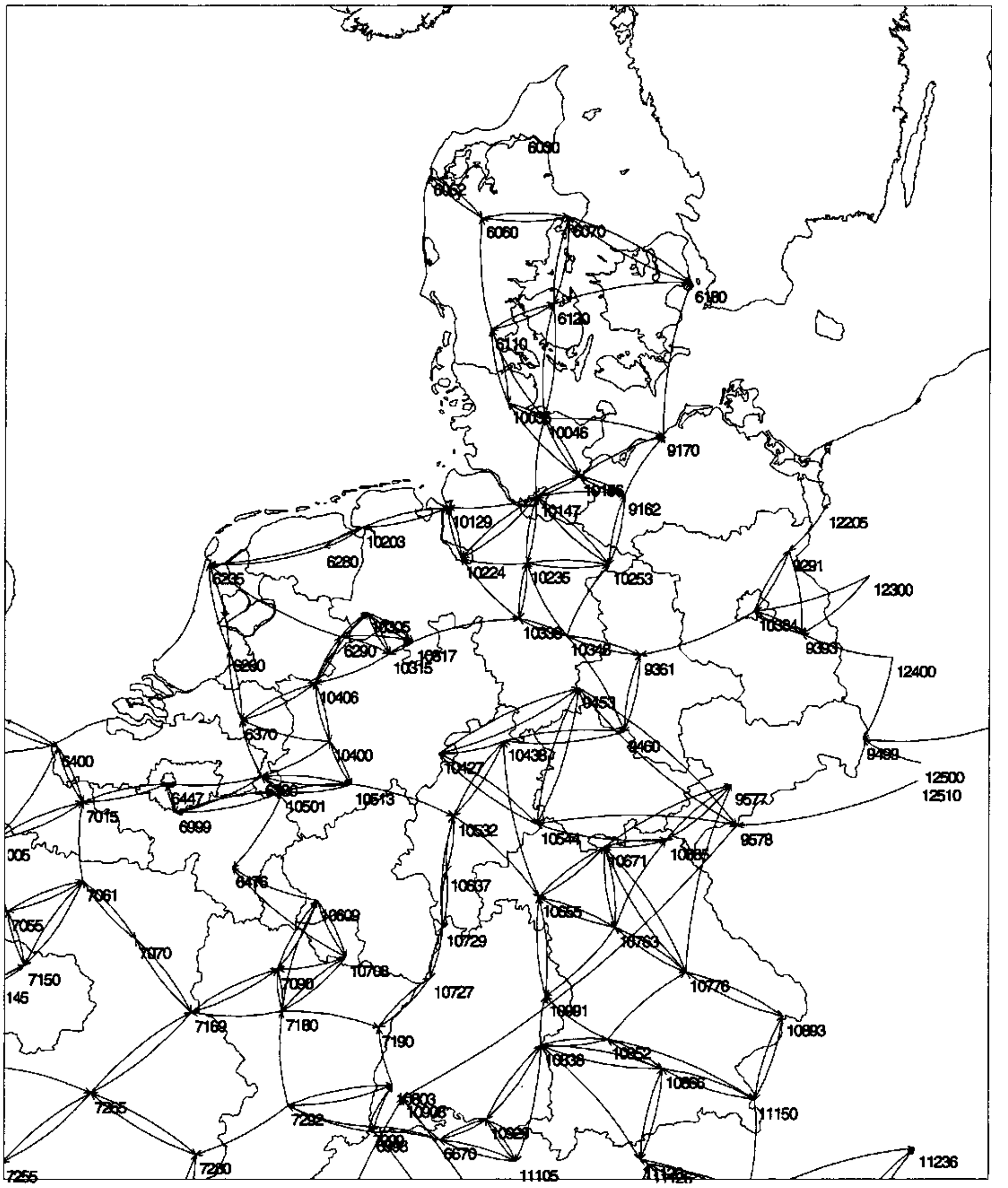
kilometers
0 600

Annex 5 Maps showing for each reference station the set of stations selected by the algorithm for interpolation of daily meteorological data



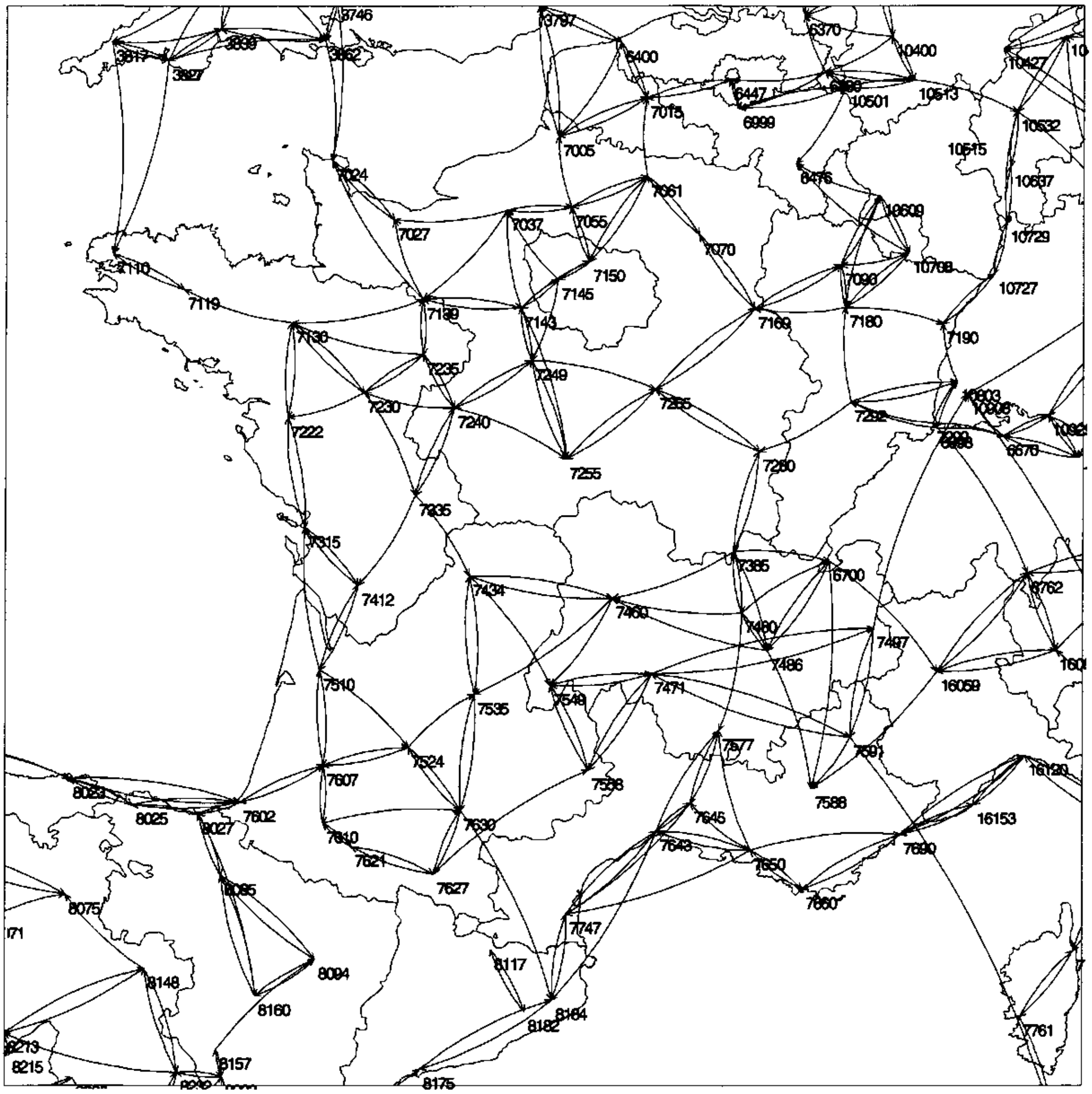
Annex 5.1
United Kingdom
Ireland

kilometers
0
600



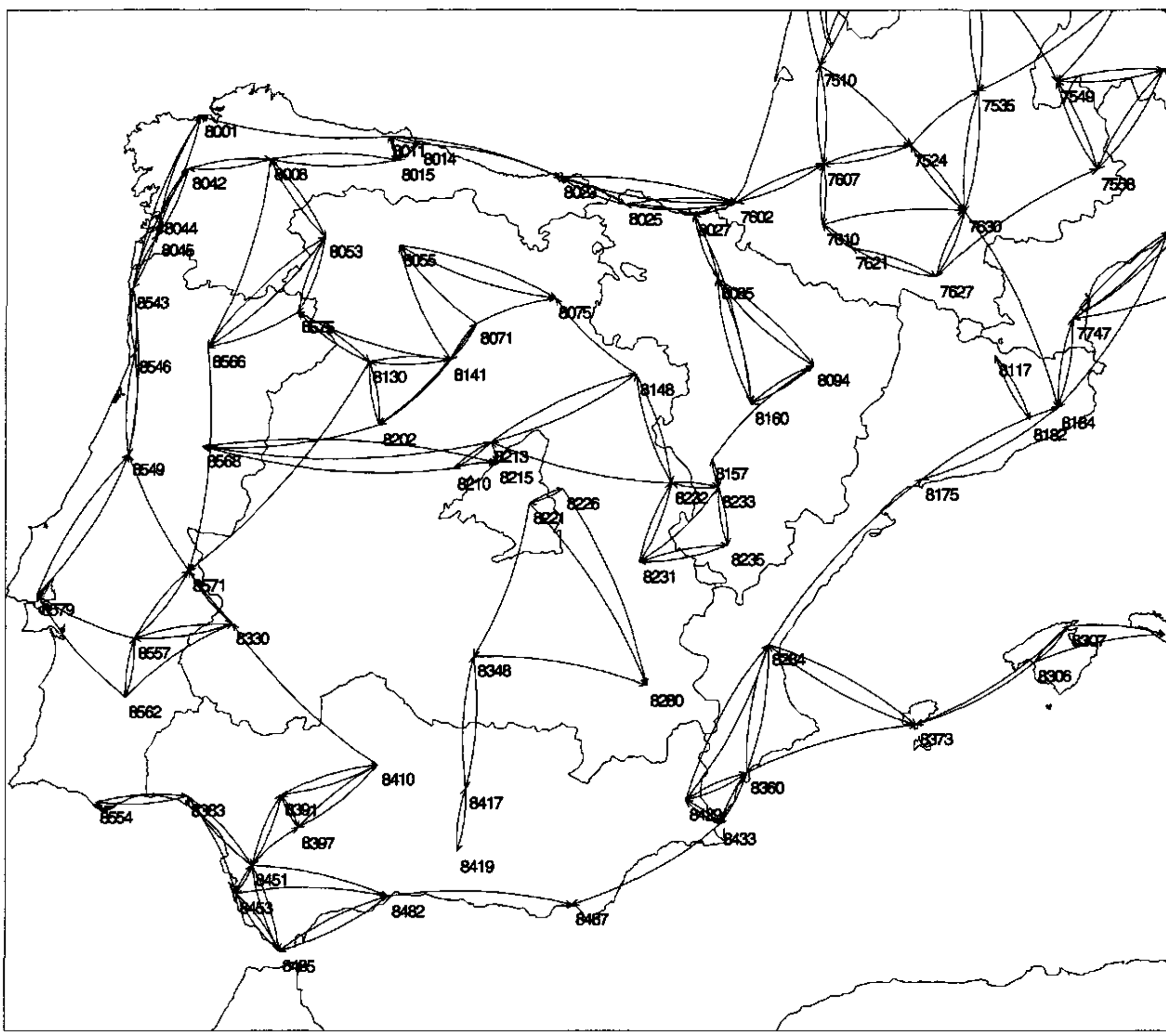
Annex 5.2
Denmark
The Netherlands
Belgium
Germany

kilometers
0 600



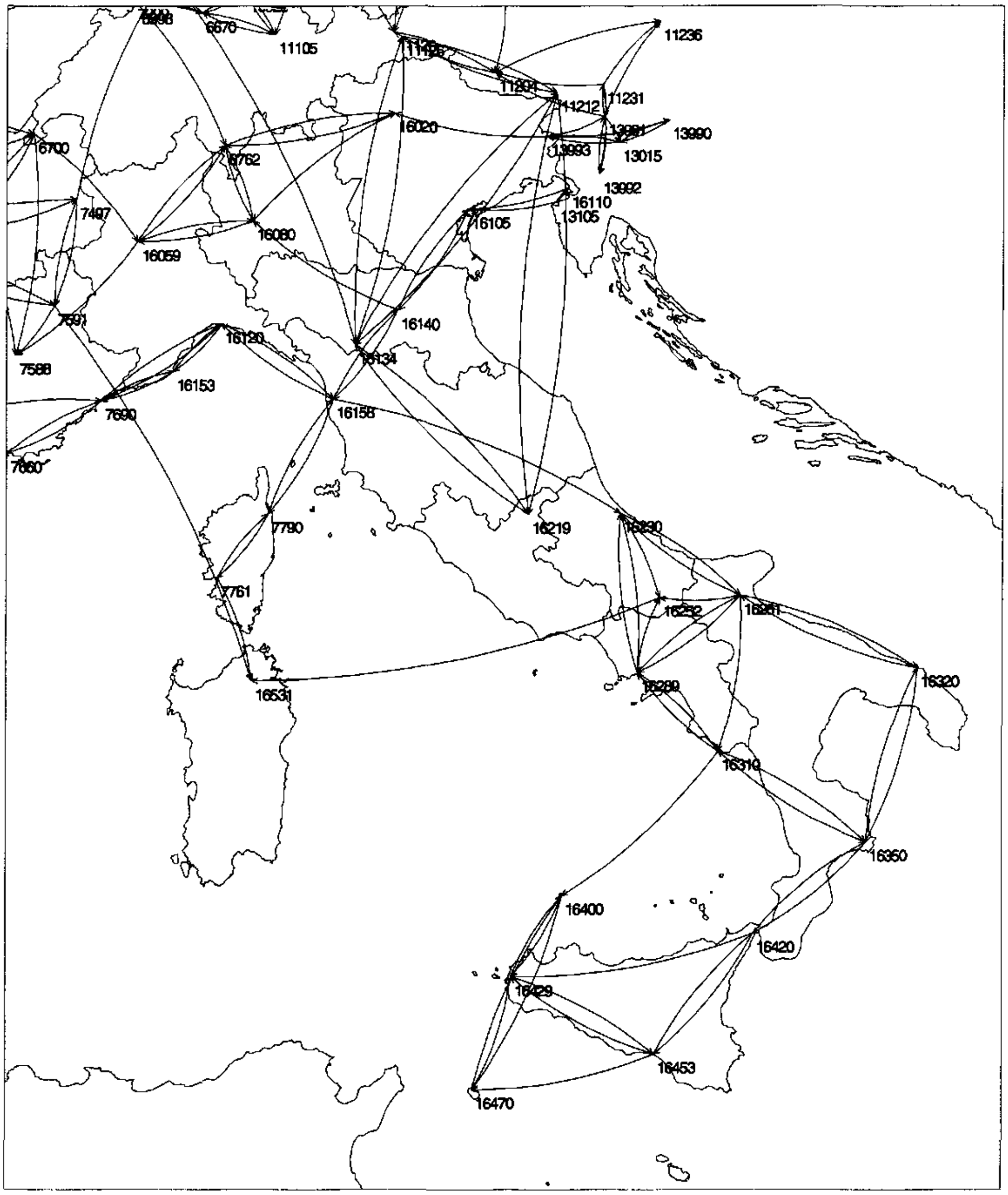
Annex 5.3
France

kilometers
0 600



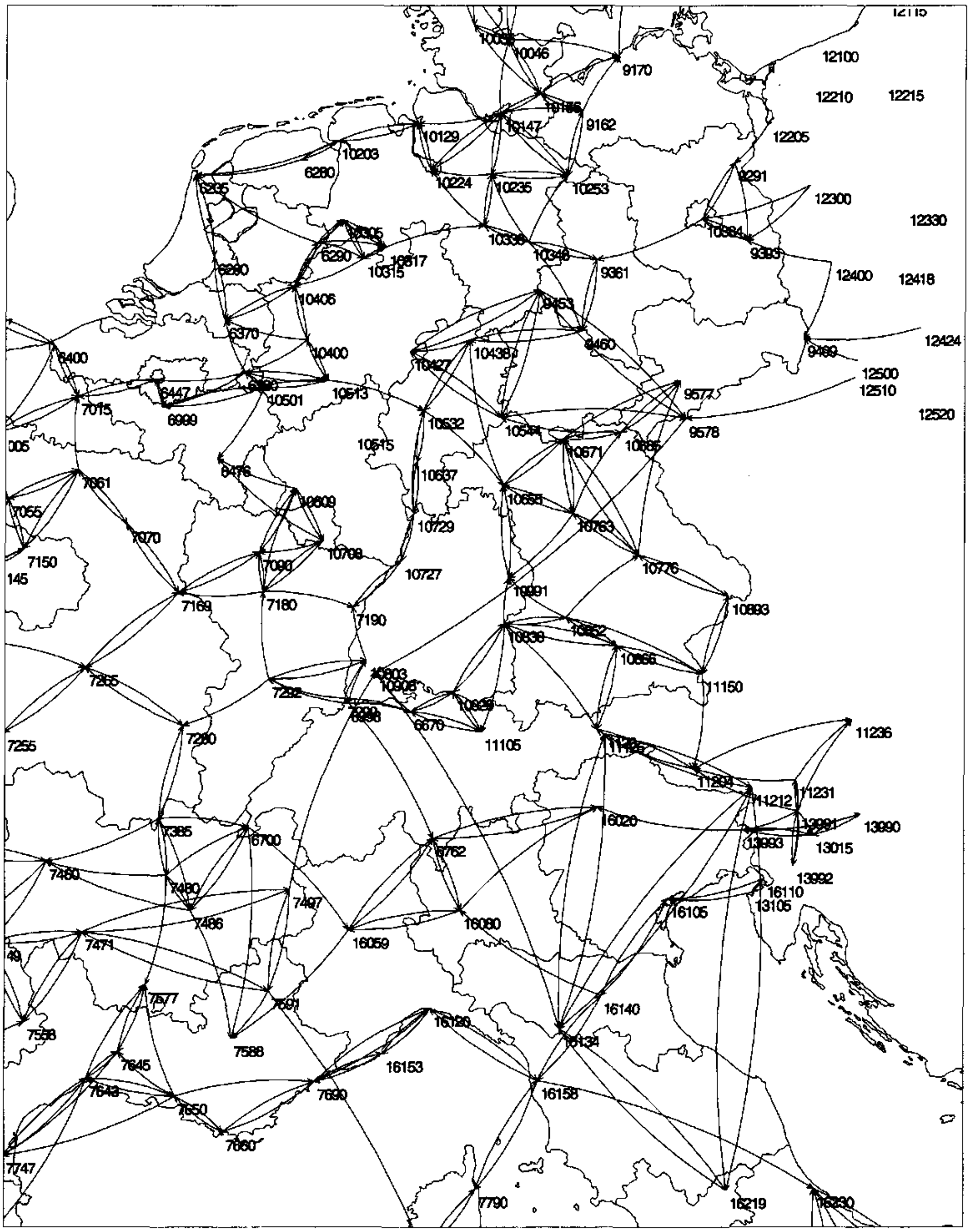
kilometers
0 600

Annex 5.4
Portugal
Spain



kilometers
0 600

Annex 5.5
Italy



kilometers
0 600

Annex 5.6
Alps and bordering area

Annex 6 Overview of the lowest absolute RMSE's per variable for all reference stations

STATION NAME	WMONR	RAD [kJ]	SSD [hr]	Tmin [C]	Tmax [C]	vap [kPa]	wind [m/s]
Kinloss	3066	3218	2.77	2.14	1.77	0.11	1.26
Prestwick	3135	2421	2.10	1.51	1.18	0.09	0.82
Leuchars	3171	2609	2.30	1.69	1.62	0.09	1.08
Carlisle	3222	2006	1.79	1.25	1.19	0.07	0.78
Newcastle	3245	2141	1.91	1.31	1.13	0.08	0.77
Leeming	3257	1717	1.53	1.22	1.01	0.07	0.72
Valley	3302	2179	1.91	1.33	1.24	0.09	1.62
Blackpool	3318	1993	1.74	1.57	1.19	0.09	0.86
Nottingha	3354	1401	1.26	1.03	0.76	0.06	0.61
Finningle	3360	1604	1.41	1.22	0.90	0.06	0.55
Shawbury	3414	1846	1.62	1.55	0.93	0.08	0.64
Aberporth	3502	2250	1.96	1.09	1.24	0.09	1.06
Birmingha	3534	1406	1.24	1.16	0.63	0.06	0.51
Wattisham	3590	2092	1.85	1.34	1.17	0.10	0.71
Brize Nor	3649	1505	1.33	0.98	0.70	0.06	0.58
Cardiff-W	3715	1961	1.68	1.11	1.09	0.08	0.84
Boscombe	3746	1382	1.20	1.01	0.74	0.06	0.57
Manston	3797	1993	1.80	1.62	1.34	0.09	1.04
St. Mawga	3817	2281	1.94	1.14	1.01	0.09	0.82
Plymouth/	3827	1742	1.49	1.11	1.16	0.07	0.88
Exeter A.	3839	1797	1.54	1.22	1.04	0.08	0.80
Bournemou	3862	1712	1.50	1.66	0.91	0.08	0.61
Belfast/A	3917	1778	1.57	1.40	0.96	0.08	0.58
Roches Po	3952	1337	1.15	0.81	0.87	0.04	1.11
Valentia	3953	2429	2.08	1.42	1.20	0.06	0.89
Cork A.	3955	1337	1.15	0.77	0.82	0.04	0.58
Rosslare	3957	2087	1.84	1.14	1.38	0.05	1.35
Kilkenny	3960	1586	1.42	1.54	1.01	0.04	0.99
Shannon A	3962	1634	1.44	0.93	0.81	0.04	0.70
Birr	3965	1282	1.13	0.94	0.61	0.03	0.66
Dublin A.	3969	1848	1.64	0.96	1.03	0.05	0.87
Claremorr	3970	1668	1.45	1.12	0.88	0.04	0.70
Mullingar	3971	1260	1.11	0.99	0.66	0.03	0.52
Clones	3974	1463	1.28	0.98	0.77	0.04	0.59
Belmullet	3976	2378	2.05	1.34	1.10	0.06	1.30
Malin Hea	3980	2443	2.05	1.48	1.66	0.06	2.28
Thyboron	6052	2614	2.23	2.34	2.15	0.14	2.03
Karup	6060	1626	1.39	1.49	1.19	0.09	0.85
Tirstrup	6070	1651	1.49	2.07	1.16	0.09	0.85
Skrydstru	6110	1780	1.56	1.53	1.26	0.08	0.72
Odense	6120	1464	1.35	1.34	1.03	0.08	0.68
Kobenhavn	6180	2348	2.07	1.67	1.52	0.11	1.03
De Kooy	6235	2336	2.04	1.64	1.74	0.08	1.71
De Bilt	6260	1430	1.27	1.02	0.92	0.06	0.65
Eelde	6280	1439	1.26	1.56	0.86	0.07	0.74
Twente	6290	1191	1.04	1.19	0.84	0.06	0.58
Eindhoven	6370	1412	1.28	1.00	0.69	0.05	0.80
Zuid-Limb	6380	1109	0.98	0.95	0.66	0.07	0.80
Koksijde	6400	2088	1.81	1.48	1.20	0.08	0.90
Uccle	6447	1325	1.20	1.02	2.70	0.14	1.38
St-Hubert	6476	1834	1.69	1.19	1.44	0.08	0.93
Zurich Ai	6670	1611	1.51	0.91	1.31	0.08	0.59
Geneve/Co	6700	2134	2.01	1.81	1.88	0.12	1.13
Locarno/M	6762	2422	2.28	2.04	2.40	0.15	0.48
Basel	6998	1333	1.24	0.79	0.81	0.06	0.79
Ernage	6999	1390	1.21	1.43	0.88	0.08	0.50
Abbeville	7005	1754	1.55	1.01	1.05	0.06	0.99
Lille	7015	1496	1.33	0.89	0.83	0.07	0.89
Cherbourg	7024	2230	1.96	1.55	1.29	0.09	1.34
Caen	7027	1826	1.67	1.16	1.20	0.07	0.99
Rouen	7037	1422	1.30	1.02	0.82	0.05	0.75
Beauvais	7055	1320	1.19	0.91	0.71	0.06	0.63
Saint-Que	7061	1442	1.30	0.98	0.82	0.06	0.74

Reims	7070	1536	1.39	1.26	0.90	0.07	0.82
Metz	7090	1276	1.17	0.97	0.84	0.08	0.67
Brest	7110	2371	2.05	1.34	1.12	0.08	0.94
Rostrenen	7119	1897	1.66	1.04	1.08	0.06	0.88
Rennes	7130	1775	1.61	1.18	1.03	0.07	0.74
Alencon	7139	1587	1.45	1.16	0.99	0.06	0.94
Chartres	7143	1213	1.11	0.77	0.66	0.06	0.71
Trappes	7145	1123	1.00	0.95	0.67	0.06	0.83
Paris/Le	7150	1264	1.16	0.90	0.76	0.06	0.80
Saint-Diz	7169	1493	1.41	1.22	1.05	0.07	0.79
Nancy	7180	1264	1.15	1.15	0.94	0.06	0.71
Strasbour	7190	1446	1.37	1.14	1.15	0.07	0.81
Nantes	7222	1806	1.61	1.20	0.96	0.07	0.79
Angers	7230	1533	1.40	0.89	0.84	0.07	0.78
Le Mans	7235	1169	1.09	1.18	0.72	0.06	0.83
Tours	7240	1285	1.18	0.94	0.80	0.07	0.73
Orleans	7249	1324	1.22	1.01	0.82	0.05	0.82
Bourges	7255	1770	1.60	1.16	1.10	0.08	0.83
Auxerre	7265	1625	1.49	1.08	1.22	0.07	0.92
Dijon	7280	1726	1.67	1.35	1.34	0.09	0.95
Luxeuil	7292	1613	1.53	1.98	1.55	0.09	0.94
Bale-Mulh	7299	1321	1.20	1.08	0.81	0.07	0.89
La Rochel	7315	2180	1.91	1.76	1.62	0.08	1.15
Poitiers	7335	1695	1.55	1.09	0.98	0.08	0.73
Macon	7385	1629	1.50	1.05	0.98	0.07	0.85
Cognac	7412	1629	1.51	1.13	0.99	0.08	0.91
Limoges	7434	1892	1.84	1.80	1.63	0.08	0.92
Clermont-	7460	2047	1.94	1.88	1.78	0.10	1.08
Le Puy	7471	1928	1.81	1.96	1.84	0.09	1.35
Lyon/Bron	7480	1504	1.42	1.20	1.07	0.08	1.22
Grenoble	7486	2031	1.94	1.48	1.44	0.08	1.10
Bourg-St-	7497	2299	2.13	1.75	2.20	0.11	1.04
Bordeaux/	7510	1972	1.76	1.25	1.14	0.10	0.68
Agen	7524	1526	1.50	1.08	1.35	0.07	0.71
Gourdon	7535	1818	1.75	1.48	1.49	0.09	0.83
Aurillac	7549	2795	2.53	2.78	3.34	0.16	0.97
Millau	7558	2381	2.30	2.11	2.05	0.10	3.01
Montelima	7577	1790	1.71	1.60	1.26	0.11	1.96
Saint-Aub	7588	1826	1.68	1.79	1.47	0.11	1.25
Embrun	7591	1950	1.74	1.84	1.73	0.09	1.57
Biarritz	7602	1699	1.53	1.34	1.17	0.10	1.01
Mont-de-M	7607	1595	1.49	1.79	1.25	0.09	0.81
Pau	7610	1450	1.33	1.07	1.03	0.08	0.88
Tarbes	7621	1291	1.18	1.27	0.96	0.08	1.05
Saint-Gir	7627	1917	1.79	1.48	1.48	0.09	0.93
Toulouse/	7630	1871	1.73	1.33	1.35	0.09	0.88
Montpelli	7643	1626	1.49	1.54	1.59	0.11	1.31
Nimes/Cou	7645	1317	1.24	1.32	1.30	0.10	1.10
Marseille	7650	1415	1.31	1.53	1.44	0.12	1.99
Toulon	7660	1759	1.60	1.62	2.02	0.19	1.78
Nice	7690	1981	1.85	1.25	1.53	0.12	1.18
Perpignan	7747	2413	2.22	2.13	1.75	0.14	2.09
Ajaccio	7761	2568	2.38	1.89	1.93	0.17	1.28
Bastia	7790	2559	2.40	1.49	1.77	0.15	1.16
La Coruna	8001	2379	2.11	1.46	1.72	0.10	1.88
Lugo Roza	8008	2147	2.00	1.99	1.87	0.08	1.72
Asturias/	8011	1665	1.45	1.18	1.15	0.07	1.54
Gijon	8014	1576	1.39	1.96	1.27	0.08	1.48
Oviedo	8015	2028	1.77	1.08	1.45	0.07	1.66
Santander	8023	2051	1.78	1.40	1.18	0.07	1.62
Sondica A	8025	1725	1.52	1.82	1.83	0.07	1.45
San Sebas	8027	1642	1.50	1.54	1.25	0.08	2.55
Santiago/	8042	1800	1.64	1.31	1.72	0.08	1.17
Pontevedr	8044	1824	1.57	1.12	1.33	0.13	1.01
Vigo/Pein	8045	2341	1.92	1.05	1.18	0.12	1.15
Ponferrad	8053	3876	3.26	1.24	1.68	0.08	1.08
Leon/Virg	8055	2048	1.94	1.49	1.49	0.09	1.42
Palencia	8071	1732	1.69	1.39	1.27	0.09	1.10
Burgos/Vi	8075	2360	2.09	1.68	1.77	0.10	1.68
Pamplona/	8085	2383	2.19	1.57	1.73	0.10	1.56
Huesca/Mo	8094	2044	2.05	1.91	1.98	0.19	2.38
La Molina	8117	2582	2.27	2.06	1.95	0.13	1.70
Zamora O.	8130	1522	1.49	1.01	1.17	0.08	0.81

Valladoli	8141	1479	1.46	1.39	1.21	0.08	0.92
Soria O.	8148	2008	1.84	1.33	1.54	0.09	1.10
Daroca O.	8157	1434	1.33	1.47	1.23	0.09	0.80
Zaragoza	8160	1708	1.74	1.47	1.92	0.11	3.03
Reus A.	8175	2631	2.44	1.80	1.61	0.14	2.06
Montseny	8182	3847	3.41	2.06	2.60	0.15	4.35
Gerona/Co	8184	2822	2.52	2.28	1.55	0.13	1.88
Salamanca	8202	1565	1.52	1.29	1.19	0.08	1.34
Avila O.	8210	1544	1.51	1.42	1.67	0.15	1.42
Segovia O	8213	1921	1.85	1.50	1.19	0.10	0.81
Navacerra	8215	2124	2.08	2.15	1.91	0.10	1.95
Madrid/Ba	8221	1465	1.41	1.61	1.07	0.12	1.33
Guadalaja	8226	1453	1.42	1.36	1.20	0.26	0.73
Cuenca	8231	1834	1.75	1.37	1.45	0.11	0.90
Molina De	8232	1480	1.41	1.67	1.06	0.10	1.10
Calamocha	8233	1171	1.12	1.59	1.02	0.10	1.52
Teruel	8235	1876	1.82	1.46	1.26	0.10	1.05
Albacete/	8280	1956	1.90	1.55	1.49	0.16	3.12
Valencia	8284	2135	2.04	1.55	1.48	0.13	1.94
Palma de	8306	1623	1.58	2.59	1.57	0.14	1.21
Pollensa	8307	1694	1.64	1.87	1.43	0.13	1.46
Menorca/M	8314	2235	2.14	1.42	1.30	0.13	1.80
Badajoz	8330	1511	1.45	1.77	1.23	0.21	1.20
Ciudad Re	8348	1616	1.56	1.52	1.26	0.11	1.20
Alicante/	8360	1596	1.50	1.34	1.21	0.13	1.60
Ibiza es	8373	1986	1.90	1.75	1.28	0.13	1.35
Huelva	8383	1701	1.59	1.19	1.38	0.12	1.32
Sevilla/S	8391	1213	1.16	1.07	1.07	0.13	1.32
Moron De	8397	1235	1.17	1.74	0.91	0.14	1.89
Cordoba A	8410	1816	1.73	1.47	1.49	0.14	1.44
Jaen	8417	1741	1.63	2.85	1.67	0.13	1.31
Granada A	8419	1613	1.56	1.71	1.38	0.21	1.46
Murcia/Al	8429	1610	1.50	1.55	1.92	0.18	1.72
Murcia/Sa	8433	2379	2.20	1.77	1.54	0.15	1.45
Jerez De	8451	1578	1.46	1.29	0.84	0.10	1.61
San Ferna	8453	1618	1.52	1.26	1.40	0.17	1.47
Malaga A.	8482	1802	1.76	2.00	2.76	0.18	2.35
Tarifa	8485	2527	2.37	2.33	3.80	0.26	5.62
Almeria A	8487	2141	2.08	1.50	2.06	0.21	1.70
Viano do	8543	1571	1.40	1.57	1.35	0.12	0.75
Porto Ser	8546	1568	1.44	1.08	1.45	0.11	1.21
Coimbra	8549	1993	1.76	1.24	1.41	0.11	1.04
Faro	8554	1835	1.73	1.56	1.47	0.14	0.81
Evora	8557	1322	1.20	0.95	0.86	0.12	0.58
Beja	8562	1542	1.50	1.25	0.96	0.13	0.71
Vila Real	8566	1715	1.61	1.27	1.28	0.19	1.01
Penhas Do	8568	1993	1.87	1.80	2.32	0.18	2.11
Portalege	8571	1509	1.43	2.83	1.28	0.19	0.78
Braganca	8575	1637	1.51	1.25	1.14	0.09	0.75
Lisboa/Ga	8579	1951	1.83	1.27	1.38	0.16	0.88
Schwerin	9162	1344	1.19	0.95	0.94	0.05	0.44
Warnemund	9170	1809	1.62	1.37	1.81	0.10	1.14
Angermund	9291	1498	1.35	1.00	0.83	0.05	1.66
Magdeburg	9361	1465	1.35	1.04	0.99	0.06	0.62
Lindenber	9393	1469	1.28	0.96	0.83	0.05	0.51
Brocken	9453	2205	2.09	1.31	2.09	0.07	2.64
Artern	9460	1951	1.74	1.14	1.25	0.06	0.84
Goerlitz	9499	1869	1.64	1.32	1.23	0.06	1.31
Karl Marx	9577	1865	1.72	1.63	1.40	0.05	0.95
Fichtelbe	9578	1894	1.88	1.10	1.63	0.07	1.12
Schleswig	10035	1562	1.37	1.00	0.86	0.06	0.58
Kiel-Holt	10046	1250	1.10	0.95	0.73	0.05	1.14
Bremerhav	10129	1559	1.32	1.08	1.22	0.07	0.96
Hamburg/F	10147	1405	1.25	0.96	0.72	0.05	0.62
Lubeck	10156	1179	1.04	0.71	0.79	0.06	0.55
Emden-haf	10203	1427	1.23	0.98	0.78	0.05	0.85
Bremen	10224	1290	1.13	1.19	0.92	0.05	0.54
Soltau	10235	1211	1.10	0.82	0.69	0.04	0.55
Luchow	10253	1456	1.29	1.39	0.83	0.05	0.48
Lingen	10305	1203	1.05	0.71	0.71	0.05	0.46
Munster	10315	1234	1.11	0.79	0.64	0.05	0.61
Osnabruck	10317	1202	1.06	0.78	0.62	0.04	0.50
Hannover	10338	1176	1.06	1.01	0.73	0.04	0.53

Braunschw	10348	1289	1.16	0.84	0.81	0.04	0.60
Berlin/Te	10384	1315	1.19	1.04	0.78	0.05	0.64
Dusseldor	10400	1185	1.05	1.06	0.79	0.04	0.64
Bocholt	10406	1195	1.07	0.99	0.68	0.06	0.51
Kahler As	10427	1875	1.69	0.98	1.27	0.05	0.90
Kassel	10438	1671	1.50	1.16	1.18	0.06	0.94
Aachen	10501	1240	1.19	1.48	0.98	0.06	0.69
Koln/Bonn	10513	1405	1.29	1.46	0.90	0.05	0.72
Giessen	10532	1515	1.35	0.91	0.87	0.06	0.62
Wasserkup	10544	1762	1.65	1.00	1.15	0.05	1.28
Trier-Pet	10609	1472	1.35	0.96	1.15	0.06	0.67
Frankfurt	10637	1284	1.18	1.26	0.74	0.05	0.70
Wurzurg	10655	1406	1.27	0.94	0.99	0.05	0.61
Coburg	10671	1543	1.40	1.02	1.10	0.05	0.65
Hof	10685	1594	1.45	1.30	1.21	0.05	0.79
Saarbruck	10708	1465	1.35	1.10	1.15	0.07	0.70
Karlsruhe	10727	1467	1.33	1.03	0.94	0.06	0.75
Mannheim	10729	1291	1.19	1.05	0.78	0.05	0.63
Nurnberg	10763	1495	1.38	1.21	0.98	0.05	0.63
Regensbur	10776	1862	1.71	1.16	1.62	0.06	0.70
Freiburg	10803	1482	1.40	1.47	1.44	0.07	0.89
Ulm	10838	1398	1.30	1.01	0.99	0.05	0.60
Augsburg	10852	1223	1.13	0.90	0.88	0.04	0.55
Munchen-R	10866	1368	1.31	1.28	1.16	0.05	0.74
Passau	10893	4177	3.64	2.69	3.11	0.19	1.06
Feldberg	10908	2098	2.14	3.04	2.97	0.11	2.86
Konstanz	10929	1499	1.48	1.00	1.37	0.06	0.56
Nordlinge	10991	1573	1.40	2.04	1.16	0.06	0.95
Feldkirch	11105	1862	1.80	1.78	1.79	0.11	0.97
Innsbruck	11120	2066	2.00	1.61	2.81	0.11	1.12
Patcherko	11126	1607	1.59	1.50	1.86	0.08	4.18
Salzburg	11150	2133	2.00	1.64	1.77	0.11	1.09
Lienz	11204	2109	2.11	2.26	2.42	0.12	1.53
Villacher	11212	2766	2.67	1.52	1.44	0.08	2.67
Klagenfur	11231	1877	1.89	1.74	1.76	0.11	0.87
Reichersb	11236	2367	2.40	2.98	2.71	0.19	1.45
Lublijana	13015	1556	1.52	1.12	1.37	0.08	0.80
Portoroz	13105	1542	1.31	0.88	1.33	0.12	2.81
Celje	13990	1884	1.82	2.32	1.65	0.11	0.73
Golnik	13991	1711	1.68	1.26	1.49	0.09	0.95
Postojna	13992	1661	1.54	2.10	1.65	0.09	1.31
Vedrijan	13993	1802	1.63	1.33	1.65	0.13	2.11
Bolzano	16020	2146	1.96	2.52	2.99	0.12	0.59
Torino/Ca	16059	2395	2.21	1.68	1.74	0.11	0.68
Milano/Li	16080	1994	2.02	1.44	1.87	0.10	0.58
Venezia/T	16105	1917	1.84	1.47	1.66	0.14	0.79
Trieste	16110	1177	1.07	0.88	1.30	0.12	1.23
Genova/Se	16120	1984	1.85	1.60	1.75	0.11	1.36
Mt. Cimon	16134	3309	2.97	1.48	1.76	0.10	2.77
Bologna	16140	2214	2.10	1.80	2.26	0.13	0.75
Capo Mele	16153	1929	1.79	2.53	1.40	0.11	1.45
Pisa/St.	16158	2151	2.00	2.05	1.75	0.12	1.02
Mt. Termi	16219	2488	2.59	1.58	1.77	0.07	2.51
Pescara	16230	2651	2.49	1.93	2.04	0.14	0.86
Campobass	16252	2274	2.22	1.99	2.23	0.13	1.40
Amendola	16261	2060	1.95	1.61	1.90	0.15	0.99
Napoli/Ca	16289	2091	2.03	1.47	1.52	0.14	0.87
Capo Pali	16310	2027	1.97	1.39	1.31	0.17	1.27
Brindisi	16320	2072	2.03	1.78	1.94	0.19	1.19
Crotone	16350	2029	1.99	1.43	1.60	0.15	1.07
Ustica	16400	1853	1.79	1.11	1.31	0.14	2.54
Messina	16420	1906	1.88	1.38	1.37	0.15	1.06
Trapani/B	16429	1691	1.66	2.05	1.51	0.15	1.02
Gela	16453	1983	1.93	1.64	2.39	0.15	1.20
Panteller	16470	2198	2.15	1.56	1.53	0.18	1.49
Olbia/Cos	16531	2313	2.16	4.47	7.12	0.23	1.48

Annex 7 Overview of stations with non-zero climatic codes

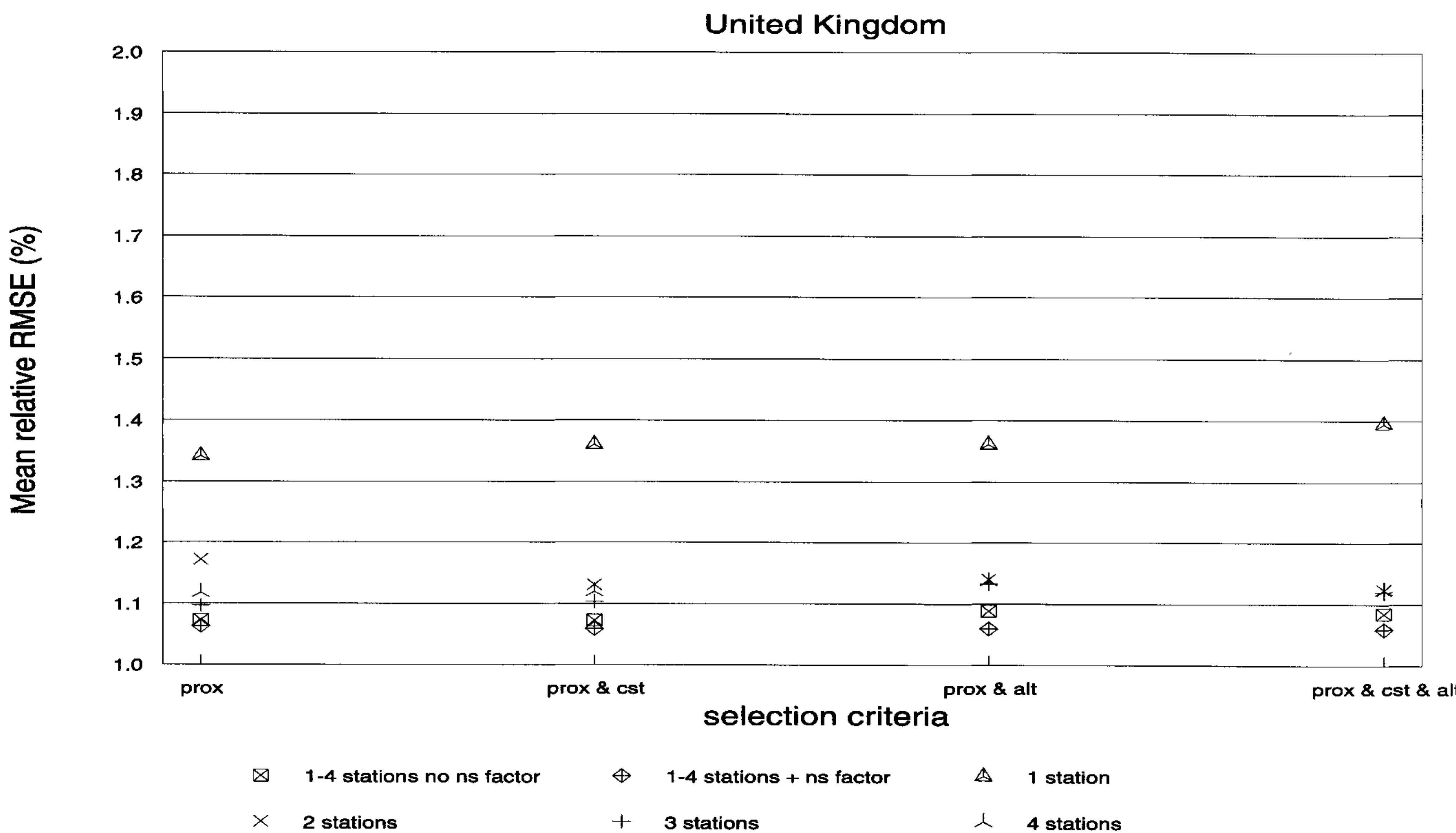
WMONR	NAME	CLIMATIC CODE
07517	Captieux	-1
07524	Agen	-1
07552	Rodez	-1
07558	Millau	-1
07607	Mont-de-Marsan	-1
07610	Pau	-1
07621	Tarbes	-1
07622	Auch	-1
07627	Saint-Girons	-1
07630	Toulouse/Blagnac	-1
07631	Toulouse/Francazal	-1
07632	Albi	-1
07640	Albi	-1
08084	Logrona/Agoncillo	1
08085	Pamplona/Noain	1
08094	Huesca/Mon Houte	1
08117	La Molina O.	1
08148	Soria O.	1
08160	Zaragoza A.	1
08171	Lerida	1
10858	Furstenfeldbruck	-2
10865	Munchen/Town	-2
10866	Munchen-Riem	-2
10868	Oberschleissheim	-2
10875	Muhldorf	-2
10893	Passau	-2
10908	Feldberg	-2
10921	Neuhausen Ob Eck	-2
10929	Konstanz	-2
10946	Kempten	-2
10947	Memmingen	-2
10948	Oberstdorf	-2
10954	Altenstadt	-2
10961	Zugspitze	-2
10962	Hohenpeissenberg	-2
10963	Garmisch/Partenk.	-2
10980	Wendelstein	-2
10982	Chieming	-2
11001	Wolfsegg	-2
11003	Ried im Innkreis	-2
11008	Rohrbach	-2
11010	Linz Airport	-2
11012	Kremsmunster	-2
11014	Koenigswiesen	-2
11015	Freistadt	-2
11101	Bregenz	-2
11105	Feldkirch	-2
11109	St. Anton am Arlberg	-2
11110	Galzig	-2
11112	Landeck	-2
11120	Innsbruck	-2

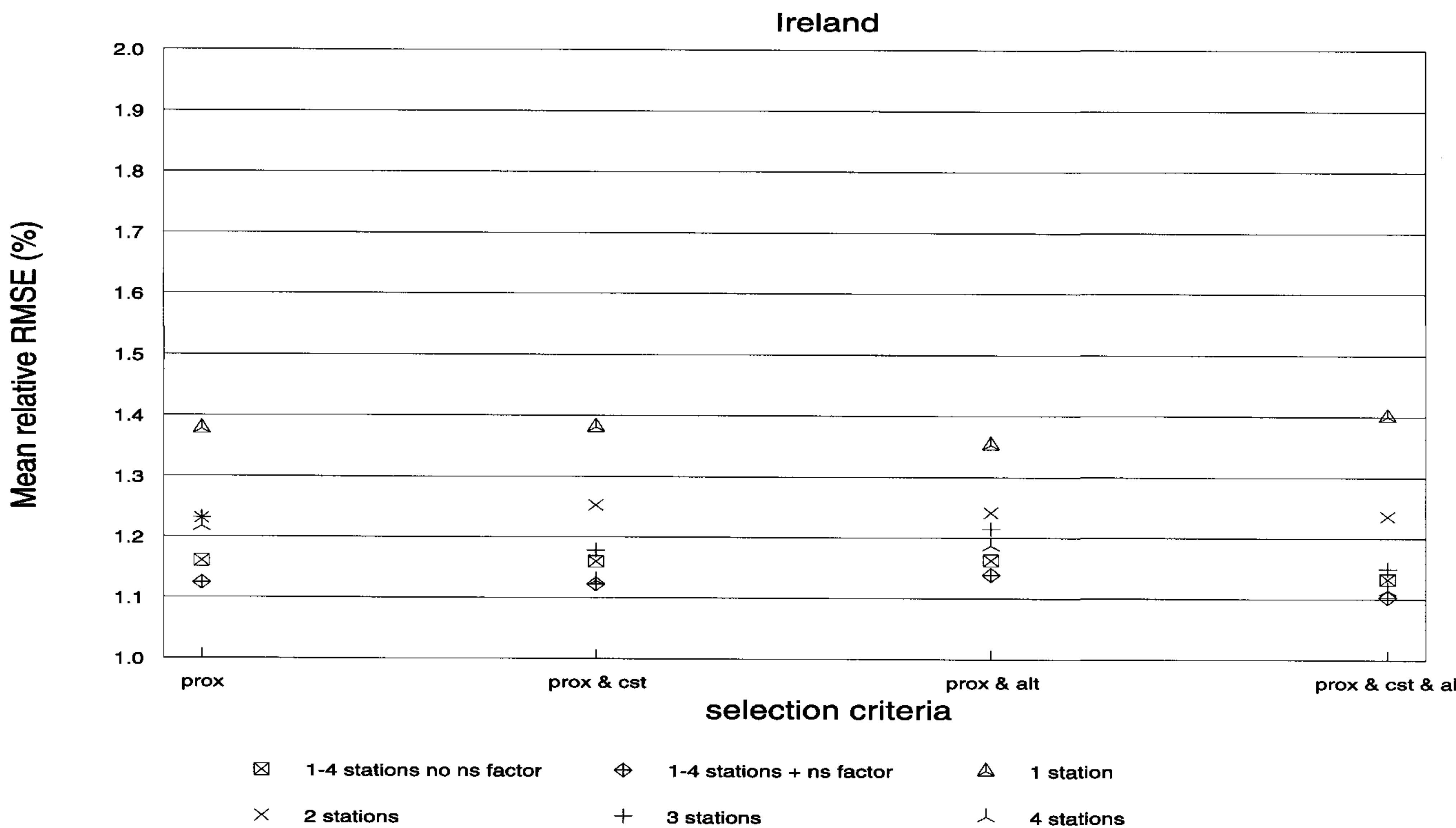
11126	Patcherkofel	-2
11127	Obergurgl	-2
11128	Brenner	-2
11130	Kufstein	-2
11135	Hahnenkamm	-2
11136	Krimml	-2
11138	Rudolfhutte	-2
11140	Unken	-2
11141	Bischofshofen	-2
11145	Bad Gastein	-2
11146	Sonnblick	-2
11147	Radstadt	-2
11148	St. Michael im Lungau	-2
11150	Salzburg	-2
11151	Seewalchen	-2
11153	Mondsee	-2
11155	Feurkogel	-2
11156	Bad Ischl	-2
11207	Reisach	2
11210	Mallnitz	2
16008	St. Valentino	2
16020	Bolzano	2
16021	Passo Rolle	2
16022	Paganella	2
16033	Dobbiaco	2
16045	Udine/Rivolto	2
16052	Pian Rosa	-2
16059	Torino/Caselle	2
16061	Torino	2
16066	Milano/Malpensa	2
16072	Mt. Bisbino	2
16076	Bergamo/Orio Al Serio	2
16080	Milano/Linate	2
16088	Brescia/Ghedi	2
16090	Verona/Villafranca	2
16094	Vicenza	2
16116	Govone	2

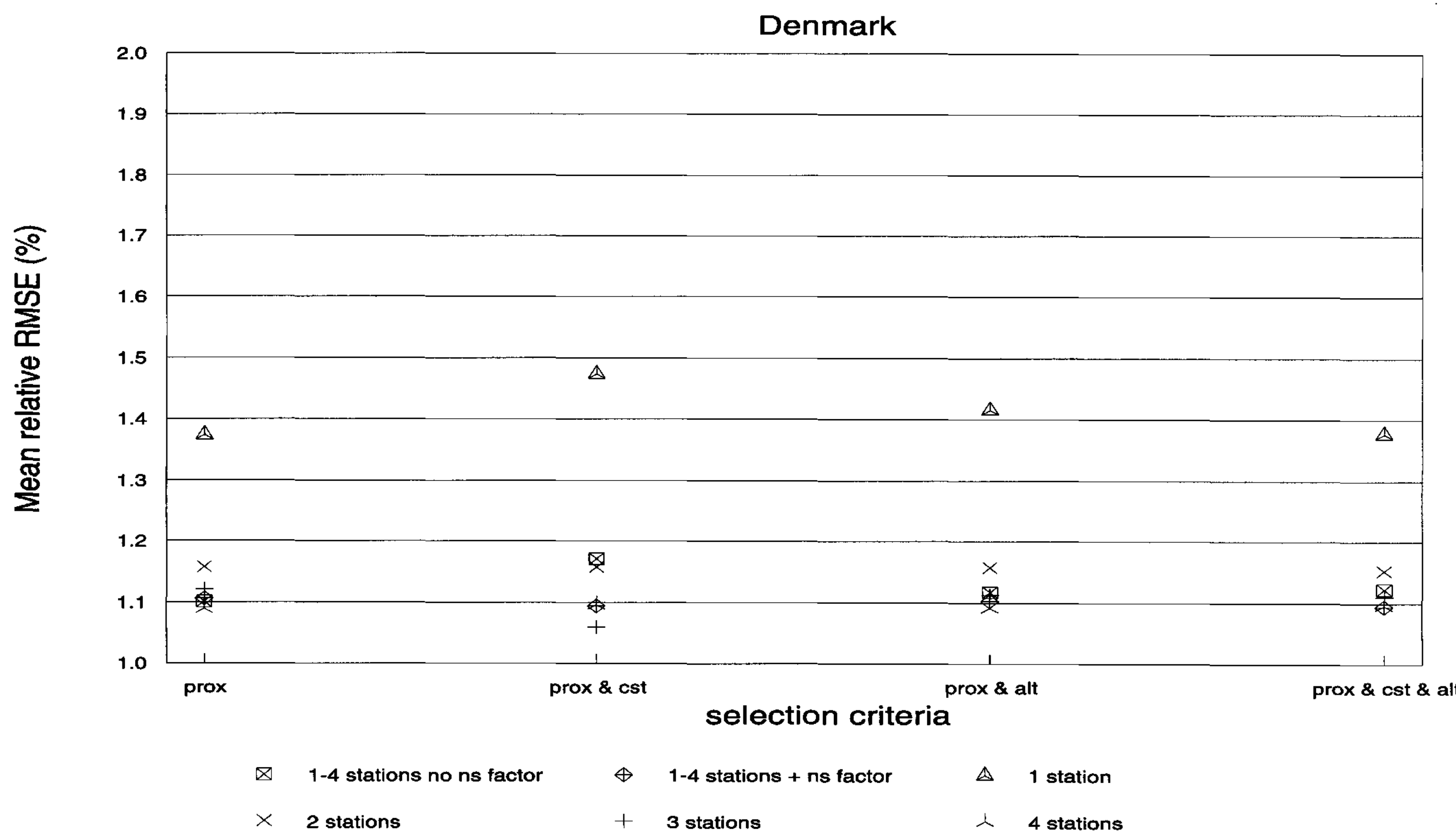
Annex 8 Overview of the median value, the mean values, and the standard deviation per country of the lowest absolute RMSE's per variable

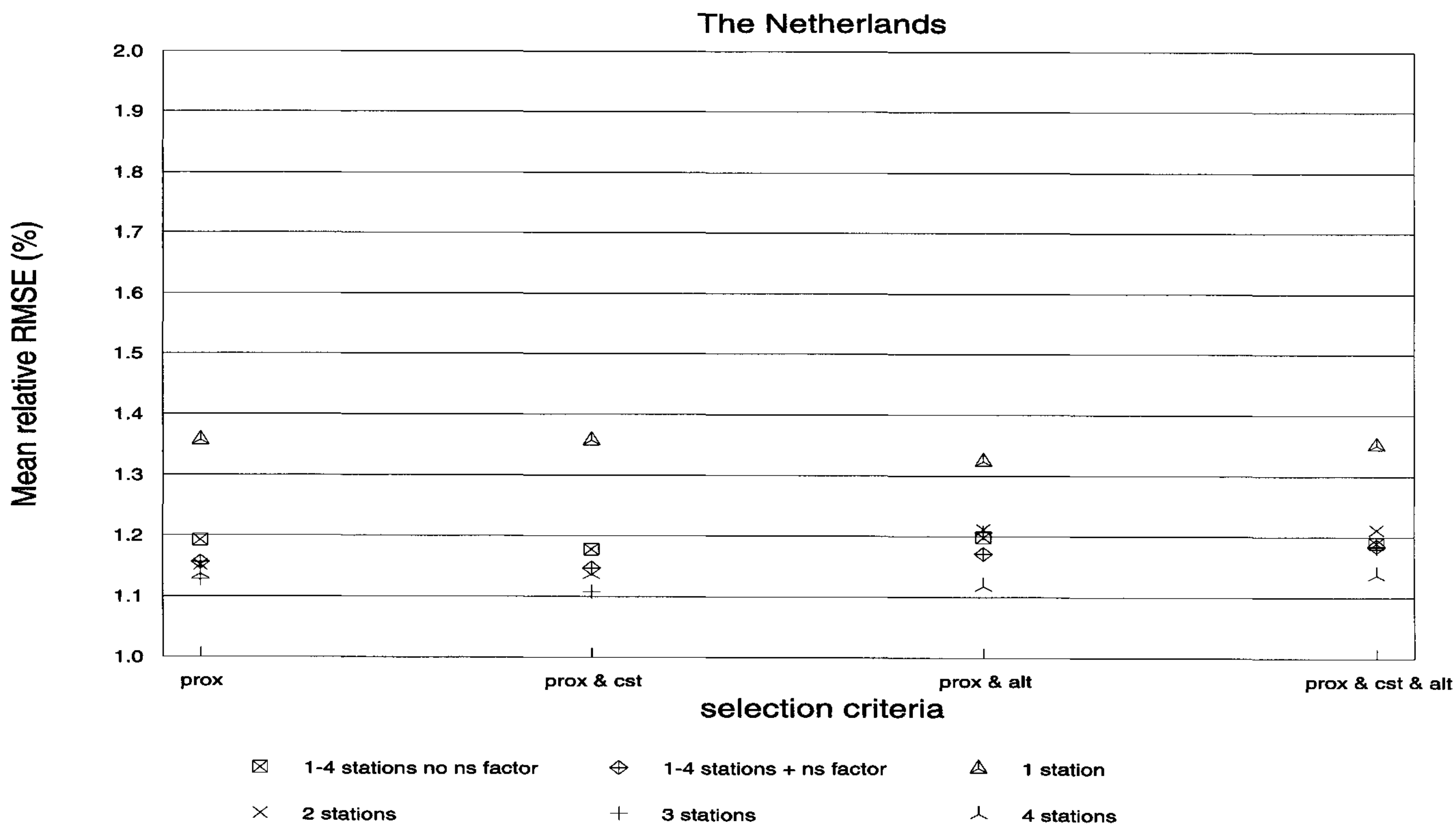
	Radiation [kJ]		Sunshine Duration [h]		Minimum Temperature [oC]		Maximum Temperature [oC]		vapour pressure [kPa]		Wind speed [m/s]	
United Kingdom												
med	3318	1961	3715	1.68	3222	1.25	3715	1.09	3715	0.08	3222	0.78
avg		1958		1.72		1.33		1.08		0.08		0.81
std		419		0.36		0.27		0.26		0.01		0.26
Ireland												
med	3962	1634	3962	1.44	3971	0.99	3970	0.88	3962	0.04	3969	0.87
avg		1750		1.52		1.11		0.98		0.04		0.96
std		429		0.36		0.25		0.29		0.01		0.46
Denmark												
	6070	1651	6070	1.49	6110	1.53	6060	1.19	6060	0.09	6070	0.85
	6110	1780	6110	1.56	6180	1.67	6110	1.26	6070	0.09	6060	0.85
med		1715		1.52		1.60		1.22		0.09		0.85
avg		1914		1.68		1.74		1.39		0.10		1.03
std		419		0.34		0.35		0.37		0.02		0.46
Netherlands												
	6370	1412	6280	1.26	6260	1.02	6290	0.84	6290	0.06	6280	0.74
	6260	1430	6260	1.27	6290	1.19	6280	0.86	6380	0.07	6370	0.80
med		1421		1.26		1.11		0.85		0.06		0.77
avg		1488		1.31		1.23		0.95		0.06		0.77
std		403		0.35		0.28		0.36		0.01		0.02
Belgium												
	6999	1390	6999	1.21	6476	1.19	6400	1.20	6999	0.08	6400	0.90
	6476	1834	6476	1.69	6999	1.43	6476	1.44	6476	0.08	6476	0.93
med		1612		1.45		1.31		1.32		0.08		0.92
avg		1659		1.48		1.28		1.55		0.09		0.93
std		316		0.28		0.18		0.69		0.03		0.31
Switzerland												
	6670	1611	6670	1.51	6670	0.91	6670	1.31	6670	0.08	6670	0.59
	6700	2134	6700	1.51	6700	1.81	6700	1.88	6700	0.12	6998	0.79
med		1873		1.51		1.36		1.59		0.10		0.69
avg		1875		1.76		1.39		1.60		0.10		0.75
std		427		0.41		0.55		0.60		0.04		0.25
France												
med	7335	1695	7292	1.53	7690	1.25	7190	1.15	7480	0.08	7265	0.92
avg		1725		1.59		1.35		1.26		0.09		0.92
std		376		0.35		0.39		0.46		0.03		0.00
Spain												
	8042	1800	8071	1.69	8487	1.50	8307	1.43	8045	0.12	8419	1.46
	8482	1802	8410	1.73	8348	1.52	8231	1.45	8221	0.12	8307	1.46
med		1801		1.71		1.51		1.44		0.12		1.46
avg		1927		1.79		1.60		1.52		0.12		1.63
std		516		0.43		0.37		0.47		0.04		0.81
Portugal												
med	8566	1715	8566	1.61	8575	1.25	8566	1.28	9170	0.10	8579	0.88
avg		1714		1.58		1.33		1.33		0.10		0.88
std		239		0.24		0.41		0.39		0.05		0.00
Germany												
med	10655	1406	10253	1.29	10671	1.02	10224	0.92	10671	0.05	10400	0.64
avg		1495		1.36		1.16		1.06		0.06		0.64
std		471		0.42		0.46		0.50		0.02		0.00
Austria												
	11120	2066	11120	2.00	11150	1.64	11105	1.79	11150	0.11	11120	1.12
	11204	2109	11150	2.00	11231	1.74	11126	1.86	11105	0.11	11236	1.45
med		2088		2.00		1.69		1.83		0.11		1.28
avg		2098		2.06		1.88		2.07		0.11		1.28
std		329		0.32		0.47		0.47		0.03		0.16
Slovenia												
	13992	1661	13992	1.54	13991	1.26	13991	1.49	13991	0.09	13991	0.95
	13991	1711	13993	1.63	13993	1.33	13990	1.65	13990	0.11	13992	1.31
med		1686		1.58		1.30		1.57		0.10		1.13
avg		1693		1.58		1.50		1.52		0.10		1.13
std		123		0.16		0.52		0.13		0.02		0.18
Italy												
med	16320	2072	16158	2.00	16120	1.60	16158	1.75	16289	0.14	16320	1.19
avg		2134		2.05		1.78		1.99		0.13		1.19
std		372		0.35		0.66		1.11		0.03		0.00

Annex 9 Influence of the number of stations and selection criteria on the interpolation per country

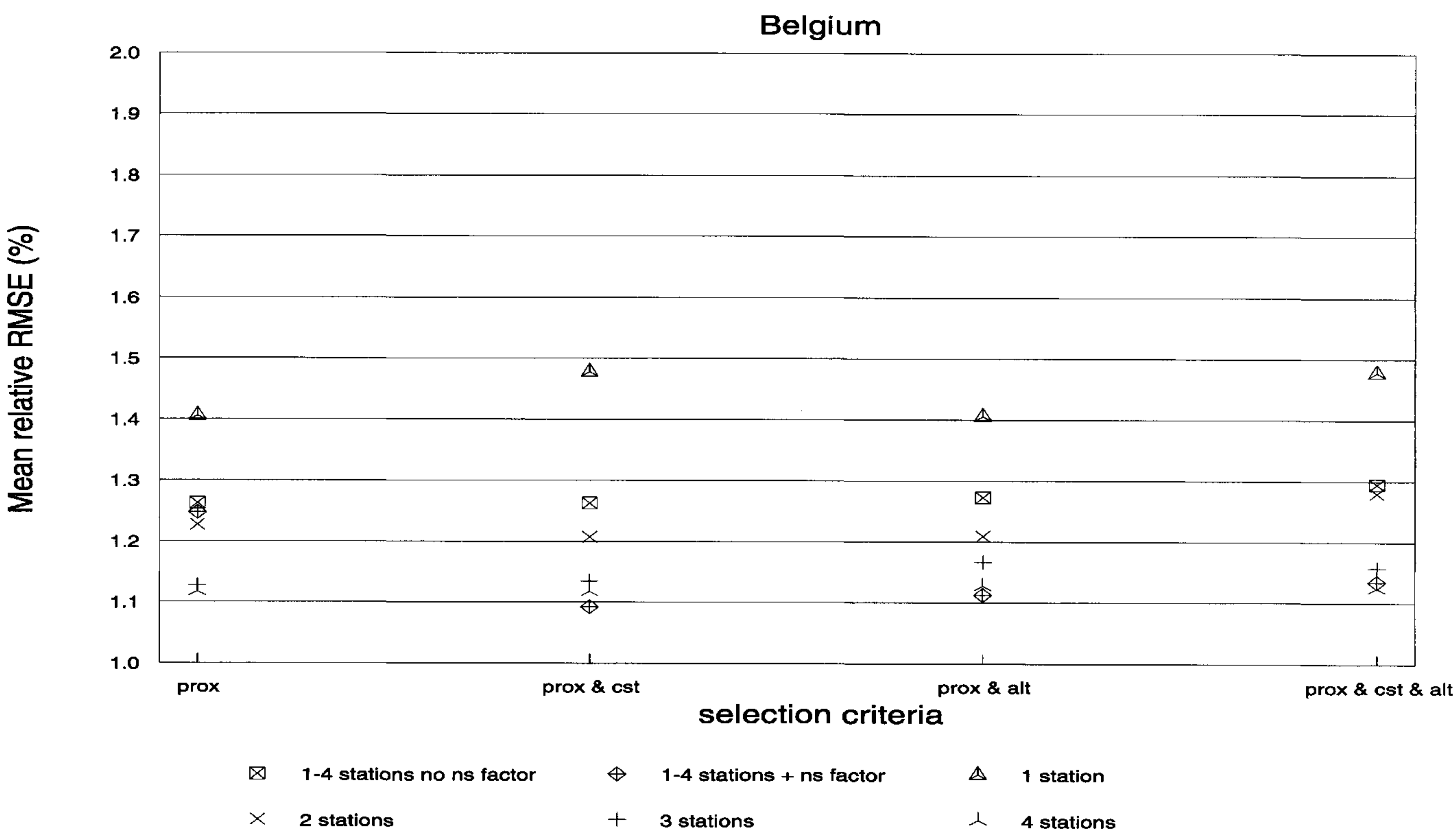

United Kingdom
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations


Ireland
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
Mean relative RMSE (%)
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations

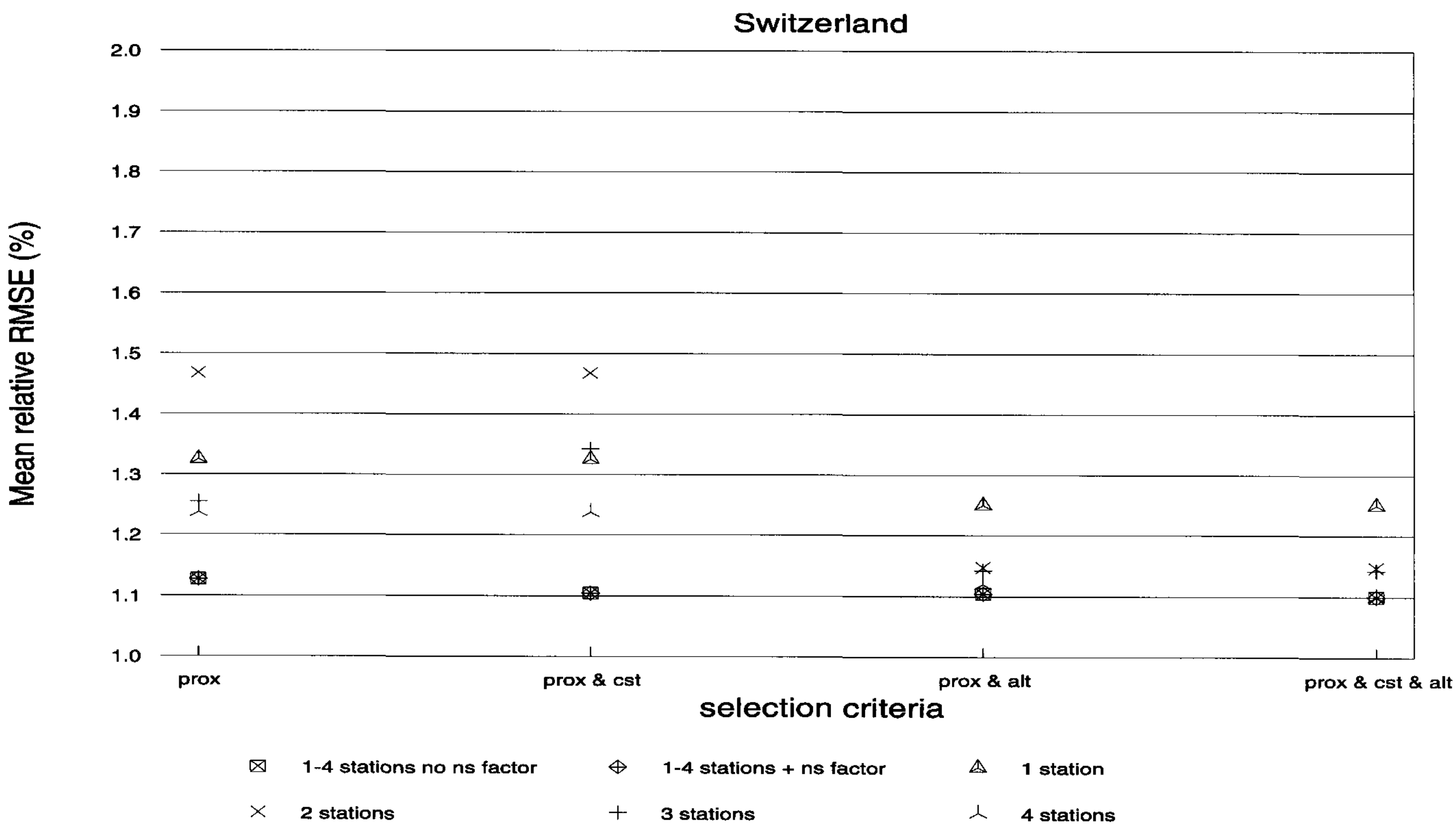

Denmark
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
Mean relative RMSE (%)
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations

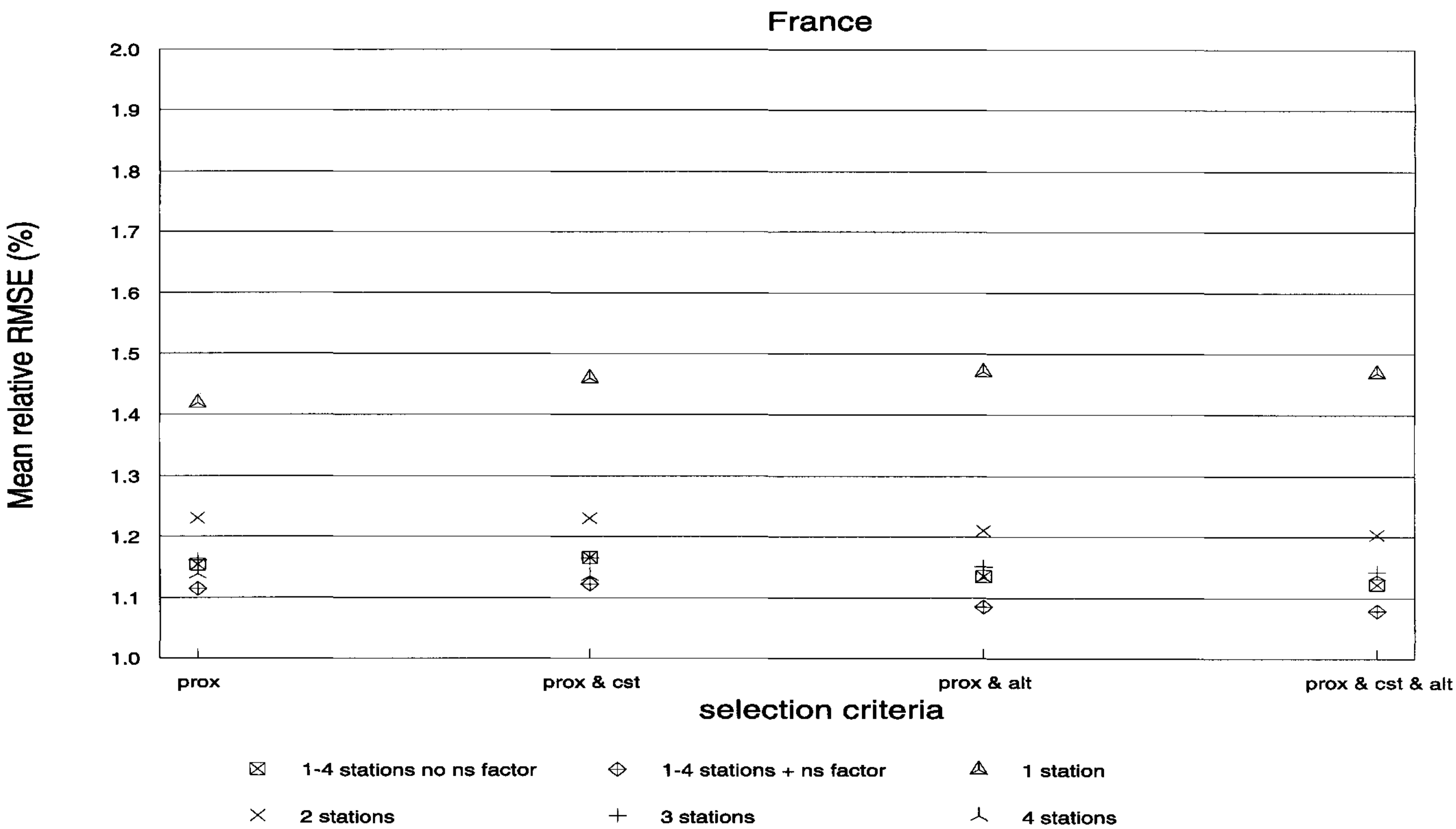


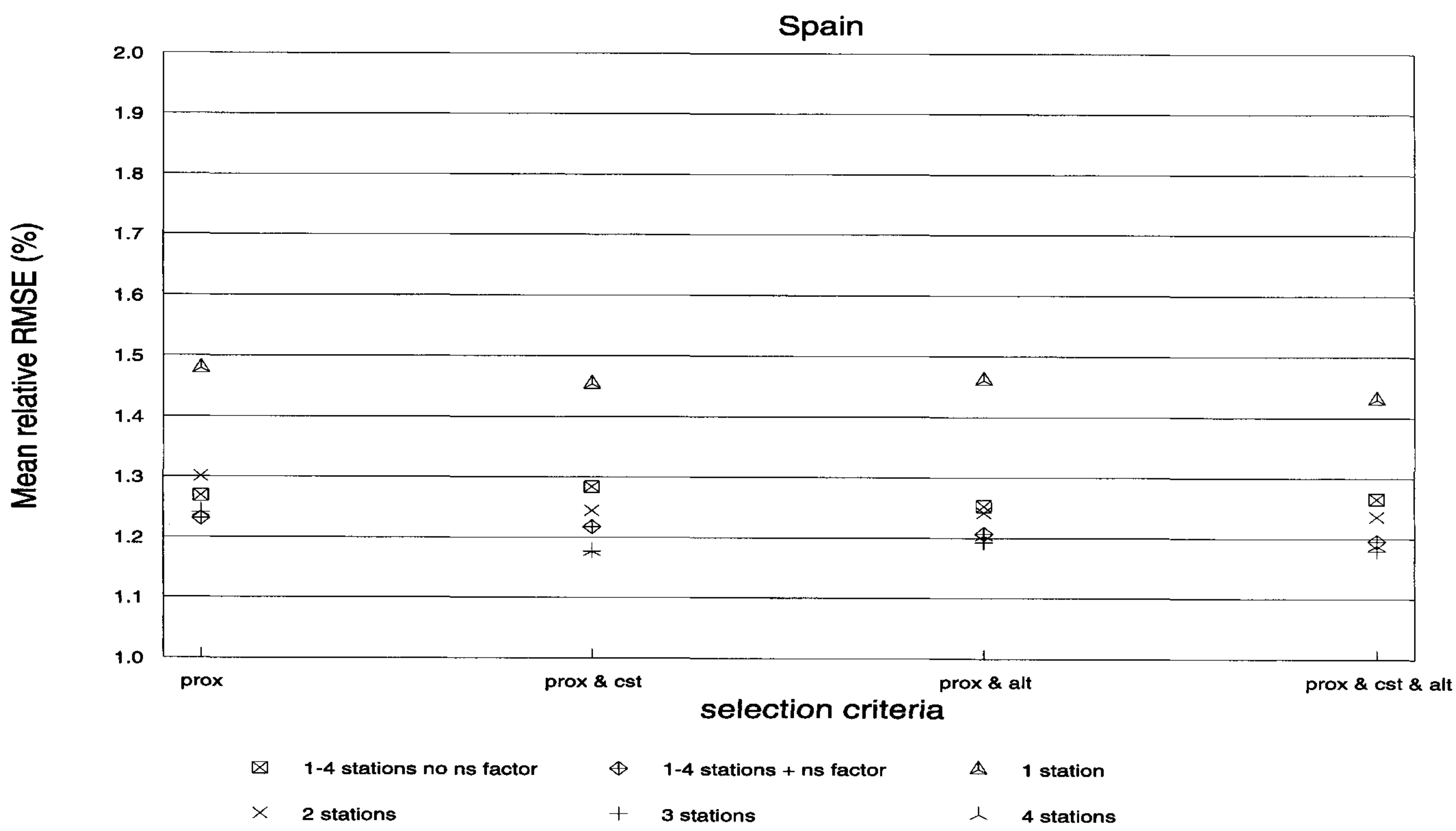
The Netherlands
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations

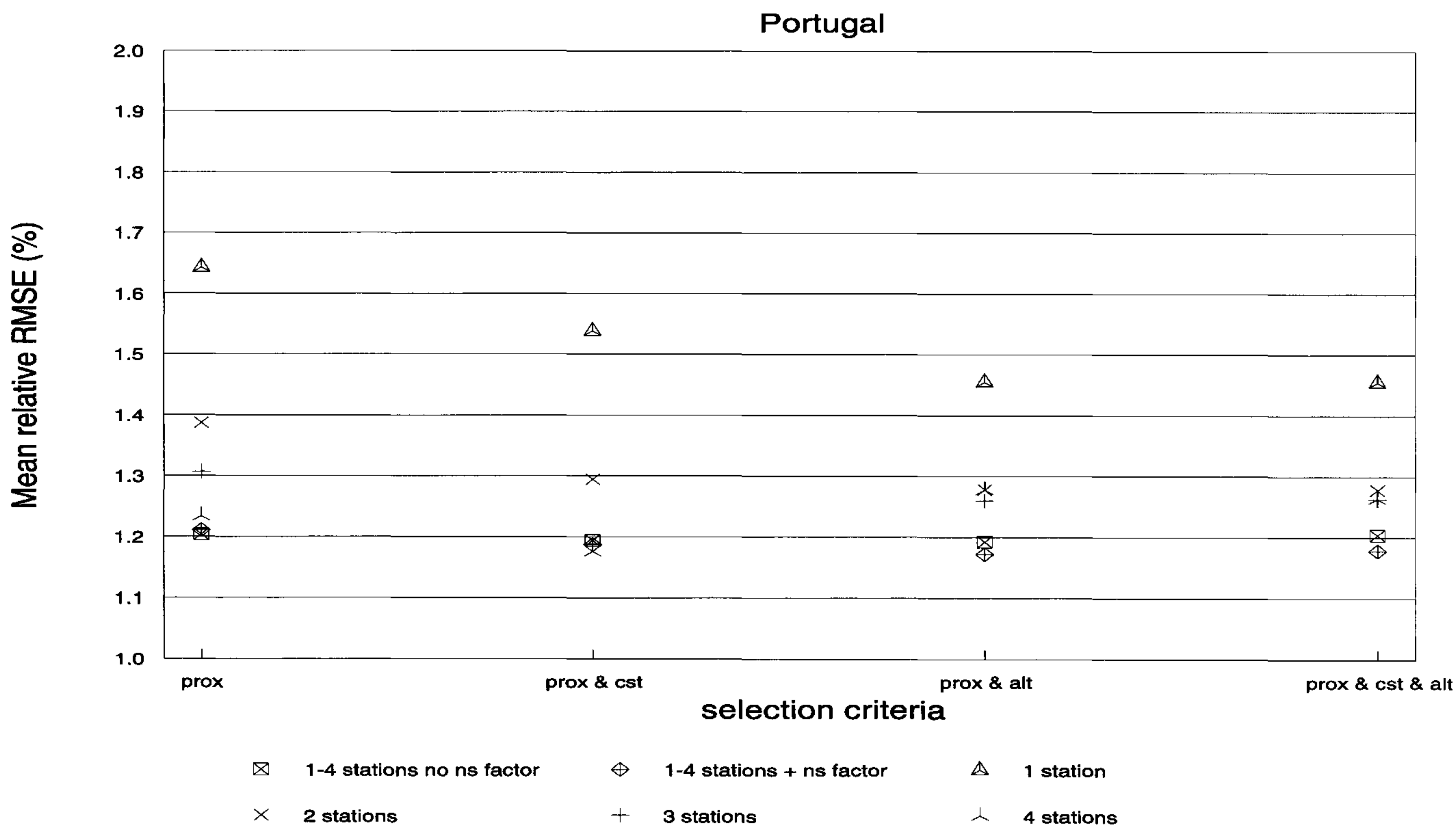


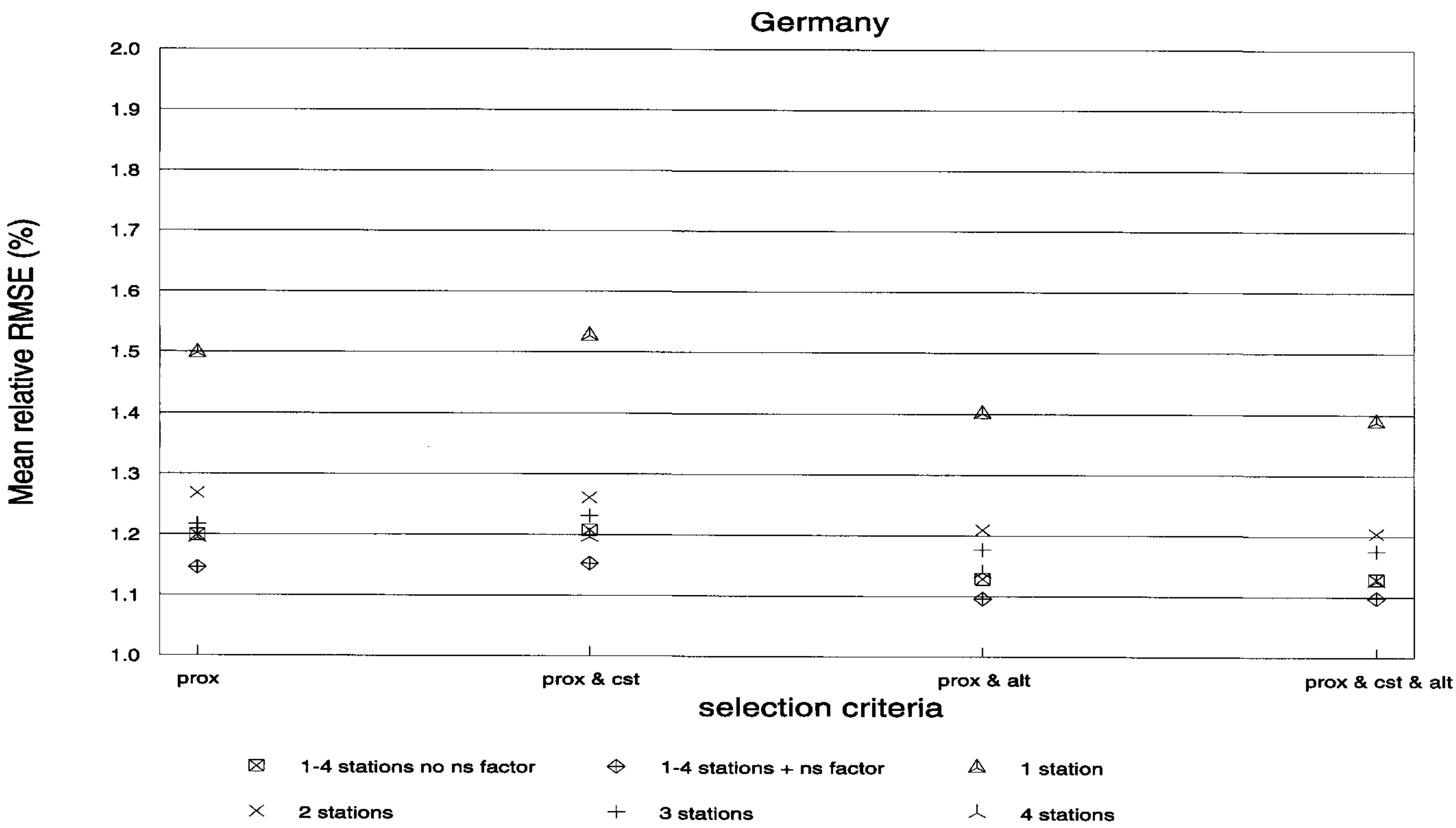
Belgium
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations


Switzerland
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations

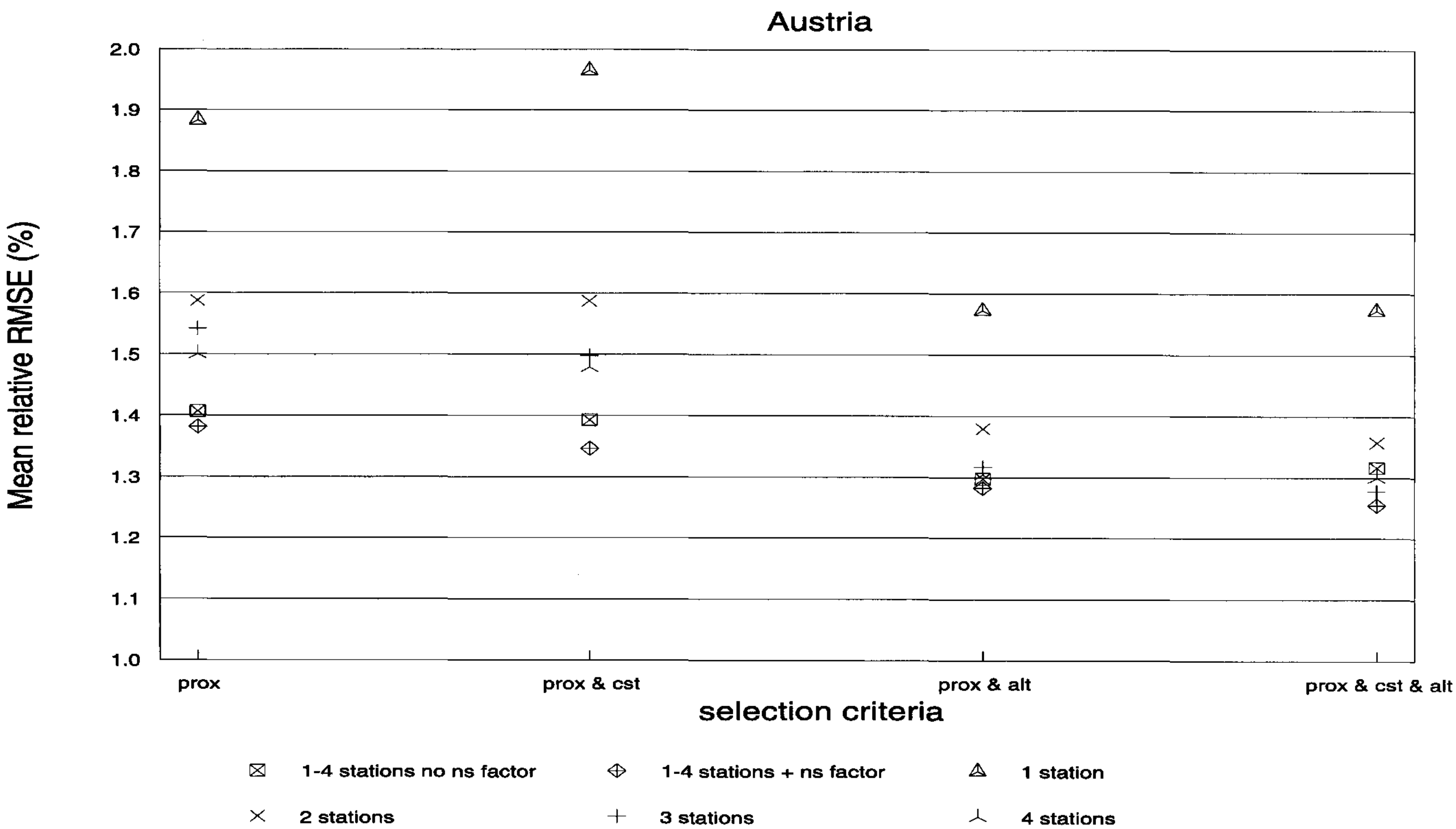

France
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations

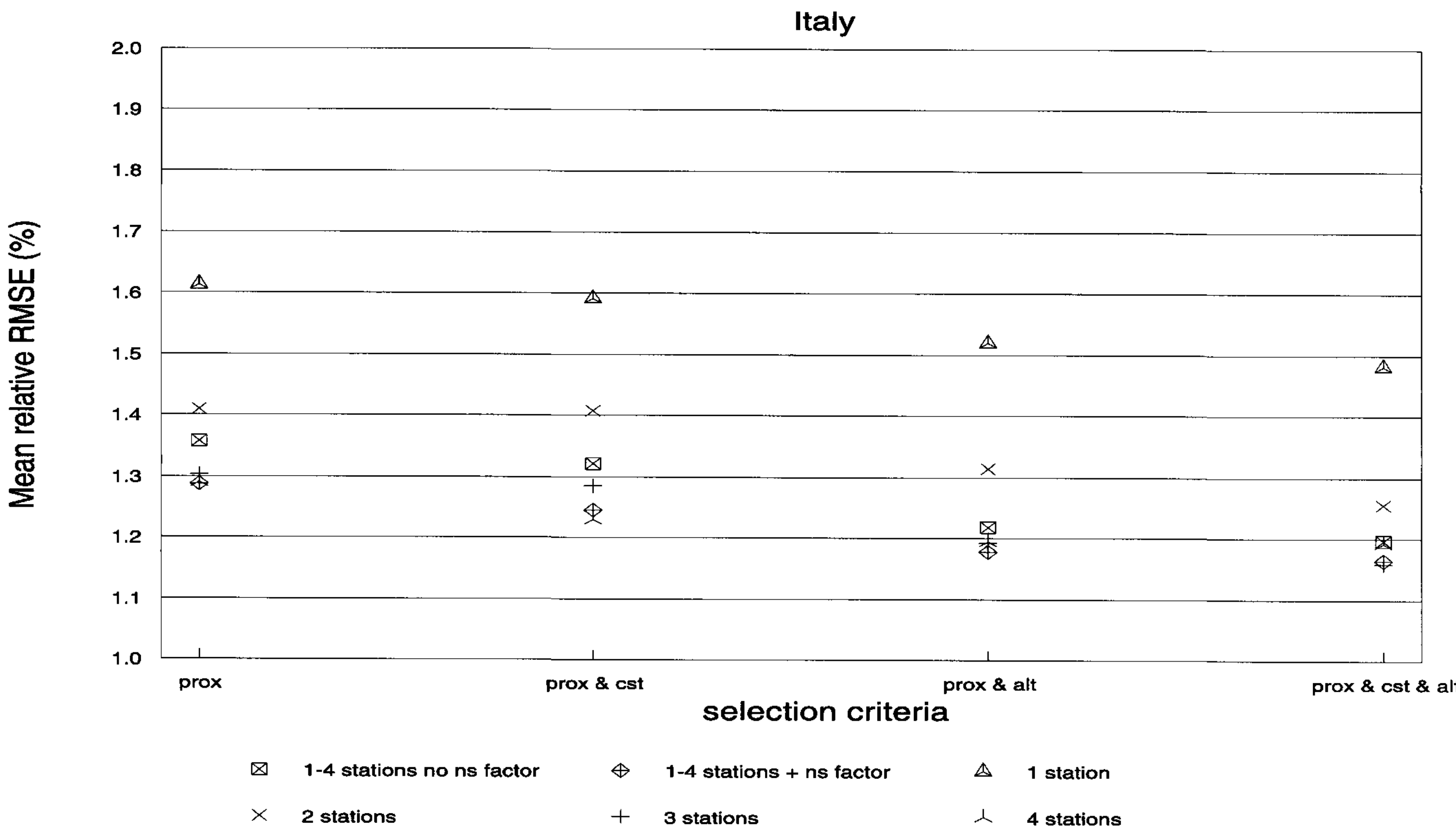

Spain
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations


Portugal
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations



Germany
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations


Austria
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations


Italy
Mean relative RMSE (%)
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
prox
prox & cst
prox & alt
prox & cst & alt
selection criteria
1-4 stations no ns factor
1-4 stations + ns factor
1 station
2 stations
3 stations
4 stations